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Economic Responsibility:

Institutional Investors' Role in the Energy Transition; Green Innovation and Decarbonization; and the Social and Economic Impact of Opioid Abuse

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Statement of Originality

I herewith declare that this thesis is my own work. All material and sources that do not constitute my own work have been explicitly acknowledged and referenced. I confirm that chapter 2 was jointly written with Patrick Bolton and Marcin Kacperczyk and that chapter 3 was jointly written with Cláudia Custódio and Dragana Cvijanović.

Moritz Wiedemann

10th of May, 2024

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Abstract

This thesis explores the role and impact of economic agents in key societal challenges. From the impact of responsible institutional investors on green capital expenditures to the nuanced dynamics of innovation and carbon emissions reduction, and the economic ramifications of the opioid overdose epidemic, each chapter reveals the interconnected nature of environmental, social, and economic factors. Together, they underscore the significance of understanding the relationship between various stakeholders and their resulting outcome to foster more sustainable economies.

In the first chapter, I study institutional investors' role in driving corporations' net zero energy transition. Exploiting regional differences in the proportion of institutional investors with sustainable preferences, I use the cross-listing of European and Asian headquartered firms in the United States as a negative responsible ownership shock. My findings suggest that responsible institutional investors can help accelerate corporate green capital expenditures by exerting influence on management.

In the second chapter, we analyse corporate green and brown R&D activity worldwide and its effects in reducing carbon emissions. We show that green innovation does not predict future reductions in carbon emissions of firms in the same sector, firms in other sectors, and across countries in the short- or medium-term. As promising as green technological breakthroughs sound, what ultimately matters for the transition to net zero is adoption of these green technologies at scale.

In the third chapter, we investigate the impact of opioid abuse on real estate prices. Using variation in opioid prescription rates induced by the staggered passage of opioid-limiting legislation, we find that a decrease in opioid usage results in an increase in county-level house prices. Consistent with improvements in local real estate quality and increases in local demand, we also document a decrease in mortgage delinquencies and vacancy rates, and an increase in home improvement loans and population inflow.

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Chapter 1

Introduction

Finance has the potential to play a major positive role in shaping and influencing large societal challenges such as climate change and public health. These major societal challenges are complex and difficult to tackle, as they are typically of global scale, involve a lot of uncertainty and a large number of agents, and include political, behavioural and technological barriers. Financial and economic theories about management of risk, resource allocation, or curbing agency problems amongst others highlight how finance can create incentives and thus has the potential to help direct capital flow to assets and economic activities that have a positive impact on sustainability. In this thesis, I seek to explore the role of different economic agents in key societal challenges, whether it is the net-zero energy transition in chapter 1 and 2 or the opioid overdose epidemic in chapter 3. From the impact of responsible institutional investors on green capital expenditures (chapter 1) to the nuanced dynamics of innovation and carbon emissions reduction (chapter 2), and the economic ramifications of the opioid overdose epidemic (chapter 3), each chapter underscores the presence of important feedback loops and reveals the interconnected nature of environmental, social, and economic factors.

A prominent example of a theoretical solution that can help us address the emission externality is the "carbon tax". Carbon taxes raise the cost of production for emission intensive operations and should thus create incentives for firms to reduce greenhouse

gases. A carbon tax therefore has the potential to restore a "first best" solution. Yet, there is also a lot of skepticism about the role of governments and financial institutions. While theoretically appealing, a carbon tax requires political will and so far has not been able to drive sufficient emission reductions. Alternatively, we may therefore need some patchwork solution based on different private and public institutions, even if this causes some efficiency loss. Other stakeholders that may push for emission reductions are non-governmental pro-climate organizations, responsible for-profit corporations, institutional investors and banks. Yet, many economic agents have (short-term) profit-driven incentives that may hamper any real process. Banks for instance continue to be major fossil fuel company financiers[1] and fossil fuel companies may lobby for a slow transition towards green technology to protect their current business models[2]. In practice, there is therefore considerable uncertainty how certain agents and their actions unfold and what their consequences are. In my three chapters, I investigate these incentives and trade-offs.

In the first chapter, I study institutional investors' role in driving corporations' net zero energy transition. Institutional investors are a key capital source and an important actor in governing public organizations. While a carbon tax requires political will, institutional investors may be an alternative source to drive emission reductions. Even if institutional investors pressure may not be as efficient as a carbon tax, they may be one important player in a patchwork solution. Indeed, there has been a phenomenal rise in responsible investing in the last two decades. However, many commentators criticize responsible investing as just green-washing[3]. My findings suggest that firms that see an increase in responsible ownership, subsequently increase green capital expenditures. Overall, my results underscore the importance institutional investors can play in accelerating green capital expenditures, which subsequently appear to translate into emission reductions.

[1] Jackson, F (2024, May 13) "Banks Back Fossil Fuels With $6.9 Trillion". Forbes.
[2] Niranjan, A (2024, March 8) "Oil industry has sought to block state backing for green tech since 1960s". The Guardian.
[3] Majority Action. (2022, March). "Fulfilling the Promise: How Climate Action 100+ Investor-Signatories Can Mitigate Systemic Climate Risk". Majority Action.

In the second chapter, I analyse with Patrick Bolton and Marcin Kacperczyk corporate green and brown R&D activity worldwide and its effects in reducing carbon emissions. The climate crisis is sometimes also referred to as a technological crisis[4]. Current technologies may not allow for net-zero production and consumption, but with the correct technological innovation this technological barrier will be broken and emissions can be reduced. The implicit assumption is that "green" innovation translates into emission reductions. We highlight in this chapter that this is an assumption and no certainty. Indeed, green innovation may actually end up in higher emissions if it stimulates demand for the product, as known as the Jevons Paradox (Jevons, 1865). Related, the Arrow replacement effect (1962) and the economics of learning by doing might drive path dependency and hinder any corporate change. Lastly, emission reductions in one part of the production network may only be "displaced" and occur at a different part of the production network. Our findings suggests that the production of green innovation may be necessary for the sustainability revolution, but it is far from sufficient. Instead, the coordination of the adoption of green innovation across companies and sectors seems critical to enable emission reductions.

In the third chapter, I turn my attention to a major public health crisis in the United States, the opioid overdose epidemic, and investigate with Cláudia Custódio and Dragana Cvijanović the impact of opioid abuse on real estate prices. Opioid usage in the United States has surged over the past two decades, resulting in more than 600,000 deaths from opioid-related overdoses since 1999. While the crisis emerged from profit-driven actors in the insufficiently regulated pharmaceutical and health-care industries, the scale of the consequences are large and multifold. We investigate how this health crisis has spilled over into the local economy, specifically real estate prices. Understanding the impact on the most valuable asset of most households' balance sheet, real estate (Favilukis, Ludvigson, and Van Nieuwerburgh, 2017), is important. Moreover, home equity can alleviate financing frictions (Mian and Sufi, 2011) and serve as

[4] e.g. Fréry, F. (2021). "Le changement climatique est un défi technologique". ESCP Impact Papers. or Schimmer, K. (2024). "Why Green Hydrogen Just Might Be the Silver Bullet Against Climate Change". WSJ Custom Content.

collateral to spur entrepreneurship (Adelino, Schoar, and Severino, 2015). We find that a decrease in opioid usage results in an increase in real estate prices. Consistent with an improvement in the quality of local premises, and an increase in the local demand for space we also observe a decrease in mortgage delinquencies and vacancy rates, and an increase in home improvement loans and population inflow following the reduction in opioid usage. Our findings show how a public health crisis can spill over into the local economy and highlights the need for policy interventions to address the economic costs of an epidemic.

Chapter 2

Green Stewards: Responsible Institutional Investors Foster Green CapEx

2.1 Introduction

There has been a phenomenal rise in responsible investing in the first two decades of the 21st century. Multiple responsible investor initiatives with growing numbers of institutional investor signatories have sprung up. The formation of the "Glasgow Financial Alliance for Net Zero" investor coalition in 2021 was a high point. Its signatories' assets under management represent roughly 40% of the total global financial asset base. Such enormous and rapid growth inevitably elicits questions and backlashes. Is responsible investing mostly a fad, an extension of culture wars, or has it resulted in meaningful changes in corporations' sustainability? While the literature has focused on the portfolio impact of responsible investors (e.g. Heath, Macciocchi, Michaely, and Ringgenberg, 2021; Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022; Atta-Darkua, Glossner, Krueger, and Matos, 2022), less is known about the influence of responsible investors on firms' capital expenditure decisions.

In this paper, I empirically investigate how the rise in ownership by responsible investors has impacted one key real outcome: green capital expenditures. Green capital expenditures are critical to replace brown operations and scale green technology. To be on target for a Net Zero by 2050 trajectory, the International Energy Association estimates annual required green capital expenditures to be about $4 trillion IEA (2022) compared to realized green capital expenditures of about $1 trillion in 2022.[1] My findings suggest that responsible institutional investors foster and therefore help accelerate firms' green capital expenditures by exerting influence on management. In addressing this question, there are three immediate empirical challenges. First, on the institutional side, who counts as a responsible investor? Second, on the firm side, what qualifies as green capital expenditure? Third, how to separate the causal impact of responsible investment from the endogenous selection of green firms by responsible investors?

My study combines global data on firm-level ownership by responsible institutional investors and green capital expenditure. I define responsible investors as institutional investors who care about global decarbonization as opposed to conventional investors who seek to maximize shareholder returns. To identify responsible investors, I exploit membership of the Climate Action 100+ (CA100+) initiative, the largest collaborative engagement group for climate change, as arguable credible signal of investors' objective. The objective of the CA100+ initiative is to "ensure the world's largest corporate greenhouse gas emitters take necessary action on climate change". In contrast to many other climate change initiatives, the CA100+ initiative includes a verifiable obligation, specifically, investors commit to engage with target companies' management on decarbonization. I use the signatories' joining date and FactSet's institutional ownership database to compute the time-varying share of responsible ownership for each firm (CA100 SHARE), the proportion of CA100+ institutional investors relative to all insti-

[1] Clean energy capital expenditures represent capital spent on deployment of low-carbon technology in the renewable energy, energy storage, nuclear power, hydrogen, carbon capture and storage, electrified transport and heating as well as sustainable materials sector. (see Catsaros, B. (2023, January 26). "Global Low-Carbon Energy Technology Investment Surges Past $1 Trillion for the First Time". Bloomberg.

tutional investors. In robustness analyses I consider broader and tighter responsible investor definitions to address the possibility that my main measure over or under counts responsible investors.

As firms do not typically disclose green capital expenditures, i.e. investments in assets that allow reduced carbon emissions, I need to develop a possible measure. I approximate green capital expenditures with recently developed debt instruments linked to environmental projects. In contrast to standard debt instruments green bonds and loans as well as sustainability bonds and loans have a "use of proceeds" clause to ensure funds are dedicated to environmental projects. Sustainability-linked bonds and loans do not finance specific projects but link financing conditions to key environmental performance indicators. I define the universe of all three debt instruments, i.e. green bonds/ loans, sustainability bonds/ loans and sustainability-linked bonds/loans, as green debt and collect data on both externally verified and self-classified instruments from Bloomberg.

Assuming that green debt issuance relative to green capital expenditures is approximately proportionate, green financing allows me to indirectly measure green capital expenditures over a long time period and across different sectors. Yet, as an approximation, there are immediate concerns regarding green debt instruments' green nature and coverage. Flammer (2021) shows that green bond issuers improve their environmental performance post-issuance. Further, most large investment expenditures are financed at least partially with debt (see DeAngelo (2022) for a list of references), so that the (green) debt financing likely captures a significant fraction of green capital expenditures. The main measure (GREENDEBT-DUMMY) is a dummy equal to one if a firm issued at least one green debt instrument in a given year. To address concerns that this measure does not capture the full range of green capital expenditures, I also gather alternative variables on green capital expenditure activities and outcomes. Specifically, I consider tighter definitions focusing on externally verified green debt only, firm-level data on clean investment and revenue ratios based on a green taxon-

omy from Corporate Knights[2], green patents from Orbis IP as well as greenhouse gas emissions from S&P Global Trucost as alternative measures.

In the last 5 years both responsible investment and green debt have grown in tandem. The average proportion of institutional ownership by CA100+ investors of firms in the MSCI ACWI index grew from 10.3% at the end of 2017 to 35.9% at the end of 2021 compared to 24.6% owned by the four large US asset managers (BlackRock, Vanguard, SSGA and Capital Group) in 2017 and 25.7% in 2021. At the same time the probability of issuing a green debt instrument rose from 1.5% in 2017 to 9.4% in 2021 for the MSCI ACWI subset.

My first empirical result is to document that responsible institutional ownership is associated with greater green debt issuance within an industry. In line with Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) and Atta-Darkua, Glossner, Krueger, and Matos (2022), institutional investors with sustainable preferences hold greener stocks within an industry. Next, I show that increases in responsible ownership correlate with increased green capital expenditures *within* firms by adding firm and industry-year fixed effects. A one standard deviation increase in the CA100+ share (22pp) is followed by a 0.9pp higher probability of issuing a green debt instrument three years later on average. Considering that on average only 2.6% of firms issued a green debt instrument per year in the sample period, this effect represents a 35% increase in the probability of issuing green debt. Moreover, adding firm and industry-year fixed effects leaves the coefficient largely unchanged despite a large increase in R2. This pattern is consistent with limited selection on unobservables (Altonji, Elder, and Taber, 2005). I further show that this finding is robust to different specifications, alternative responsible investor measures and alternative green investment proxies, i.e. clean investment ratios, green innovation and greenhouse gas emissions. My results are consistent with the view that responsible owners affect firms' green investment but inconsistent with the alternative view that responsible investing is cheap talk.

[2]For more information see: https://www.corporateknights.com/sustainable-economy-intelligence/

This correlation could be partly driven by omitted variables. Certain firm characteristics, e.g. management strategy changes, may jointly increase responsible ownership and green capital expenditures. To isolate the causal impact of responsible investing, I exploit a plausibly exogenous change in the proportion of responsible institutional investors through firms cross-listing in a different region. Institutional investors in Europe and Asia are on average more likely to declare sustainability interests than their American counterparts (GSIA, 2021; Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022). The regional difference in investor sustainability is the key source of variation. I propose that cross-listing in the United States should increase the proportion of American investors and therefore decrease the proportion of responsible institutional investors within a firm. While the decision to cross-list is endogenous and affects firms in multiple ways, the key identifying assumption is that a firm's decision to cross-list does not affect or reflect their green investments other than through responsible institutional investors. Researchers have identified a variety of reasons why firms may choose to cross-list in the United States. Popular motivations for firms to list abroad include lower cost of capital, greater investor recognition, improved access to capital, improved liquidity, improved governance mechanisms, or economic synergies (see e.g. Pagano, Röell, and Zechner (2002), Karolyi (2006), and Sarkissian and Schill (2016)), but do not directly involve targeting responsible investors or green investment opportunities. My sample includes 96 European and Asian headquartered firms that cross-list in the United States between 2007 and 2021.

I implement the identification strategy with a staggered difference-in-differences estimation approach following Sun and Abraham (2021b). I first identify the control group by choosing the three nearest neighbors based on one-year ex-ante firm characteristics LOGSIZE, INVEST/A, ROE and LEVERAGE after exact matching on the region (Asia or Europe) and the 2-digit SIC industry. I then estimate the interaction-weighted estimator to avoid early-treated firms acting as controls for late-treated firms. Treated firms have on average a roughly 9pp higher American investor share and a 5pp lower responsible investor (CA100+) share relative to the control group three years after

cross-listing. Further, the probability of issuing a green debt instrument is about 5pp lower and absolute scope 1 emissions are 41% higher on average over the same period. The cross-listing sample captures a subset of European and Asian firms, where the unconditional likelihood of issuing green debt is higher than in the worldwide sample. While the coefficients are accordingly larger for the difference-in-differences estimation, the results are qualitatively similar to my earlier results. To the extent that we can take this as causal evidence, it suggests lower responsible shares affect companies decisions on green capital expenditures.

This result raises the question of how responsible investors affect companies' green investment decisions. There are two plausible mechanisms. Responsible investing can affect firms' green capital expenditures by lowering the cost of capital for green projects due to the higher demand (e.g. Heinkel, Kraus, and Zechner, 2001; Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2021) and through corporate engagement, i.e. investors entering a discussion with management to push for green capital expenditures (e.g. Chowdhry, Davies, and Waters, 2019; Biais and Landier, 2022; Broccardo, Hart, and Zingales, 2022; Oehmke and Opp, 2022). Active governance allows shareholders to introduce internal governance mechanisms to direct managements' capital expenditure decisions. In line with the latter channel, one dimension of stewardship and the differentiating characteristics of the CA100+ initiative is investor engagement with management. I show the role of corporate engagement along three dimensions. First, I use the Principles for Responsible Investment survey to document that within the survey subset CA100+ signatories engage more with management than non-CA100+ signatories. Second, I document that responsible ownership is associated with stricter future environmental governance, specifically decarbonization targets as well as executive environmental responsibilities and compensation targets. Third, I find that the relationship between responsible ownership and green debt issuance is strongest for the highest emission firms, the subset investors with a limited amount of time and budget for engagement should target to achieve material emission reduction.

Concrete examples that highlight the impact of responsible ownership and the role

of engagement are the success story of the power company "Enel" and the struggle with the conglomerate "Berkshire Hathaway". Both companies are target companies for change of the CA100+ initiative. Asset manager Robecco started to engage with Enel under the CA100+ initiative in 2018. Responsible ownership at Enel was 18% in 2018 compared to an average responsible ownership of 8% (12% for the MSCI ACWI sample). Enel has made significant improvements including a more ambitious verified decarbonization target, three green bond issues between 2018 and 2022 and a decrease in scope 1 emissions by 46% between 2018 and 2021. Moreover, the CA100+ initiative evaluated Enel's capital investments in 2022 for the first time net-zero aligned.[3] In contrast, Berkshire Hathaway, which is a CA100+ target since 2017, has made very little progress and consistently rejects pushes by investors.[4] Berkshire Hathaway has not yet a verified decarbonization target and its capital investments were evaluated to be not net-zero aligned. Responsible ownership at Berkshire Hathaway is below average with 5% in 2018. The company has not issued any green debt between 2018 and 2022 and scope 1 emissions decreased only by 16% between 2018 and 2021. Enel, with a relatively large share of responsible ownership and active long-term engagements, is reshaping its environmental impact suggesting that responsible investors are not just about window-dressing. In contrast, responsible investing had little if any impact on Berkshire Hathaway, where the firm-level responsible ownership was relatively modest. This points towards the role of responsible ownership at the firm-level beyond its impact on general green asset demand.

Lastly, I investigate the relationship between responsible investor pressure and other net-zero transition pressures, such as regulation and consumer boycotts. Responsible investors may be substitutes or complements to other net-zero transition pressures. Stricter environmental regulation and societal pressure make green business models more profitable. This effect may reduce the perceived necessity for responsible in-

[3] Enel (2022, November 9) "Enel recognized as the first company to fully align disclosures". Enel Press Release

[4] Hodgson, C. (2021, March 2021) "Powerful investor group finds net zero pledges distant and hollow". Financial Times

vestors to act. Alternatively, stronger other pressures may strengthen responsible investors' position, ambition and negotiation with management as incentives for firms to invest in green projects are higher. I find that the correlation between the responsible investor share and green debt is stronger more recently, in Europe, in tight environmental regulation countries, and for firms exposed to more climate change campaigns from NGOs. This points to responsible institutional investors being most effective in conjunction with other net-zero transition pressures and thus complementary to them.

This paper relates to different strands of literature. First, it contributes to the growing literature on the role of institutional investors in the net zero transition. The theoretical literature on socially responsible investing focuses on two main strands: exclusion and impact investing. Both can generate firm investments in green activities. The exclusion literature, pioneered by Heinkel, Kraus, and Zechner (2001), studies the effect of portfolio divestment or tilting away from brown firms. Exclusion typically increases the firm's cost of capital as firms cannot access capital from responsible investors with the remaining investors requiring higher risk premia to absorb the divested shares (e.g. Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; De Angelis, Tankov, and Zerbib, 2022; Broccardo, Hart, and Zingales, 2022; Zerbib, 2022)). Pástor, Stambaugh, and Taylor (2021) show that even without managerial preferences for ESG, a rise in responsible investors creates positive social impact through two sources. Greener firms raise more capital and firms invest to become greener. They further hypothesize that social impact should be even greater if management has ESG preferences, which could for instance be induced by shareholder engagement. The second theoretical strand investigates how investors can finance capital and engage with management to change firm behavior (e.g. Biais and Landier, 2022; Gollier and Pouget, 2014; Chowdhry, Davies, and Waters, 2019). Here, large responsible investors subsidize firms to adopt clean technologies by accepting lower rates of return. Oehmke and Opp (2022) identify conditions under which responsible investors can induce firms to reduce externalities and invest in clean technologies. Gupta, Kopytov, and Starmans (2022) highlight that the impact of responsible investing is not unam-

bigious as responsible investors may cause strategic delays in firm reform. I provide novel empirical evidence on the real green impact of responsible investors and highlight the role of engagement in how responsible owners drive firms' green capital expenditures.

The empirical literature on socially responsible investing has mostly focused on the portfolio impact. Krueger, Sautner, and Starks (2020), Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) and Cenedese, Han, and Kacperczyk (2023) study how institutional investors, respectively investor initiative signatories, incorporate climate risk in their portfolio holdings. Heath, Macciocchi, Michaely, and Ringgenberg (2021) and Kim and Yoon (2023) study the portfolio allocation, respectively the behaviour impact on firms, of sustainable mutual funds and find mixed evidence on green-washing concerns. Pastor, Stambaugh, and Taylor (2023) measure ESG-related tilts at the portfolio level. Other papers study how institutional investors affect ESG related firms outcomes. Dyck, Lins, Roth, and Wagner (2019), Ceccarelli, Glossner, Homanen, and Schmidt (2022) and Gillan, Sekerci, and Starks (2023) consider ESG ratings, in particular the environmental and social components, as outcome. Flammer, Toffel, and Viswanathan (2021) and Ilhan, Krueger, Sautner, and Starks (2023) study how institutional investors can help improve firm-level climate risk disclosure. A few studies also look at emissions as outcome. Azar, Duro, Kadach, and Ormazabal (2021) assess the role of the Big Three asset managers, while Gantchev, Giannetti, and Li (2022) document differential firm responses to E&S incidents conditional on E&S-conscious institutional ownership. Atta-Darkua, Glossner, Krueger, and Matos (2022) suggest that climate-conscious investors decarbonize their portfolio by re-weighting their portfolio towards lower carbon emitting firms. Several papers also document how institutional investors engage with company boards and executives and influence them on different ESG dimensions (Dimson, Karakaş, and Li, 2015, 2021; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2021; Becht, Franks, Miyajima, and Suzuki, 2023). I employ a novel identification strategy based on firms' cross-listing and am the first to document that responsible institutional investors foster green capital expendi-

ture. While emissions are the ultimate end goal in the net zero energy transition, green capital expenditures shed light on how firms reduce emissions. The increase in green capital expenditure suggests that firms do not merely divest emission intensive assets, but also aim to reduce their current operations' emissions.

Second, I contribute to the literature on how corporations incorporate climate risk and transition towards net zero. A growing literature explores how climate-related commitments affect firms' actions. These include Ioannou, Li, and Serafeim (2016), Ramadorai and Zeni (2021), Comello, Reichelstein, and Reichelstein (2021), and Bolton and Kacperczyk (2023a). Accetturo, Barboni, Cascarano, Garcia-Appendini, and Tomasi (2022), Kacperczyk and Peydró (2022), and De Haas, Martin, Muûls, and Schweiger (2023) study the role of credit in shaping firms' environmental and social performance. Other papers study the impact of natural disasters, respectively physical risk, on firm outcomes (e.g. Ginglinger and Moreau, 2019; Pankratz and Schiller, 2021; Custodio, Ferreira, Garcia-Appendini, and Lam, 2022). Wang, Wurgler, and Zhang (2023) show that policy uncertainty hampers green investments. In contrast to these studies, I focus on the role of instutitonal investors as moderator. My findings suggest that institutional investors are one driver of firms' green investments and shed light how firm's decarbonize with green capital expenditures.

Third, I contribute to the literature on green bonds. Several papers study green or sustainability-linked bonds' premium (e.g. Zerbib, 2019; Fatica, Panzica, and Rancan, 2021; Baker, Bergstresser, Serafeim, and Wurgler, 2022; Berrada, Engelhardt, Gibson, and Krueger, 2022; Kölbel and Lambillon, 2022). Flammer (2021) examines the rational for issuing corporate green bonds and finds that companies signal their commitment toward the environment by issuing green bonds. In the same vein, Lu (2023) suggests that green bonds can be seen as a form of climate commitment. Fatica and Panzica (2021) show that green bond issuance is associated with a reduction in emissions. Barbalau and Zeni (2022) and Allen, Barbalau, and Zeni (2023) study the features of green bonds, respectively sustainability linked bonds, theoretically. To the best of my knowledge, I am the first to interpret green debt instruments as an indirect measure of firms'

green capital expenditures and show how responsible institutional investors moderate this. Although responsible institutional investors are under a lot of scrutiny for their real impact, I find that they practice stewardship and are a positive force in driving green capital expenditures.

2.2 Background and Data

2.2.1 Identifying responsible institutional investors

Responsible investment captures many different types of investors and styles of investing. For instance, the Global Sustainable Investor Alliance defines sustainable investment as an investment strategy that "considers environmental, social and governance factors in portfolio selection and management". I define responsible investors more narrowly as institutional investors who care about global decarbonization and declare that they want their portfolio companies to be net zero by 2050 as opposed to conventional investors who only care about maximizing shareholder returns. As I am unable to observe investors' minds, I rely on investors' actions and words to determine a credible signal that identifies responsible investors while addressing cheap talk concerns. I exploit the signing up to the CA100+ initiative, a major investor initiative with a decarbonization objective and a costly verifiable obligation, namely corporate engagements, as credible signal.

The literature has largely followed two main approaches, revealed preferences or self-declarations, to identify sustainable oriented investors (see Appendix Section A.1.1 for a detailed discussion). The "revealed preference" stream exploits investors undelrying holdings to classify responsible investors (e.g. Yang and Koci, 2020; Albuquerque, Koskinen, Yang, and Zhang, 2020; Cao, Titman, Zhan, and Zhang, 2019; Hwang, Titman, and Wang, 2022; Döttling and Kim, 2022; Gibson, Krueger, and Mitali, 2020; Kaustia and Yu, 2021; Pástor and Vorsatz, 2020; Gantchev, Giannetti, and Li, 2022), but thereby introduces a circular nature. The "self-declaration" stream gen-

erally classifies investors as responsible based on being a member of a responsible investor initiative (e.g. PRI initiative by (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022; Kim and Yoon, 2023; Liang, Sun, and Teo, 2022; Dimson, Karakaş, and Li, 2021), CERES by (Flammer, 2021), CDP/CA100+ (Atta-Darkua, Glossner, Krueger, and Matos, 2022)). The latter approach allows to abstract from investors' underlying holdings, but many initiatives have a relatively weak governance structure and merely require members to sign the initiatives' objective and pay annual fees. The lack of formal requirements leaves ample room for greenwashing.

The CA100+ initiative is also an investor initiative, but it is arguably more rigorous. Next to its decarbonization objective, the CA100+ initiative requires investors to engage with target companies' management on decarbonization. This costly verifiable obligation addresses cheap talk concerns. While the CA100+ initiative is not without critics[5], it is credited with the potential to drive change[6] and can claim several successful corporation engagements. Launched in December 2017 with 225 signatories, CA100+ has grown to more than 700 signatories and represents the largest collaborative engagement group on climate change. The signatories engage over the long-term with the world's largest greenhouse gas emitters to "improve governance on climate change, curb emissions and strengthen climate-related financial disclosures".[7] In contrast to many other sustainable initiatives, the narrow emission reduction objective and engagement component are suggestive of a "real impact mandate" Oehmke and Opp (2022). These characteristics indicate that this initiative serves as a good measure of responsible institutional investors in my context.

Having made that choice, there are immediate concerns that the responsible investor measure is over or under-inclusive. Some institutions with a clear decarbonization objective may not be signatories. For instance, the Norges Bank Investment Manage-

[5]Critics challenge the lack of transparency and milestones as well as the voting behavior of some signatories (see e.g. Majority Action. (2022, March). "Fulfilling the Promise: How Climate Action 100+ Investor-Signatories Can Mitigate Systemic Climate Risk". Majority Action.)

[6]Mooney, A. (2020, August 8). "Corporate eco-warriors driving change from Shell to Qantas". Financial Times.

[7]Cliamte Action 100+. (2017, December 12). "Global Investors Launch New Initiative To Drive Action On Climate Change By World's Largest Corporate Greenhouse Gas Emitters".

ment is a prominent advocate in tackling climate change, but is not a signatory. On the other hand, the initiative may also be over-inclusive. The two large index providers BlackRock and State Street Global Advisors are members, but their role in active governance is unclear. This noise leads to attenuation bias, which draws the coefficient towards zero and should result in underestimation of the coefficient size. Still, I construct several alternative measures to address measurement concerns. For robustness, I consider only early signatories that have been shown to be more committed in other initiatives (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022), drop/ add key institutions, exploit investors' holdings to identify and drop high churn-rate or high emission, investors, restrict the initiative to the signatory subset that is active in engagements, and build an alternative measure based on the PRI signatories and their survey responses.[8]

I collect institutional ownership data from FactSet and follow Ferreira and Matos (2008) to identify the annual level of institutional ownership from 13F and Mutual Fund Holdings data. I calculate the total firm-level institutional ownership as well as firm-level institutional ownership for CA100+ and PRI signatories with the signatory list and sign-up date. Figure 2.1, Panel A, shows the proportion of AUM of institutional investors who signed the CA100+, respectively PRI, initiative has risen over time and represent 33%, respectively 71%, in my sample in 2022. My main measure is the responsible ownership share, defined as the annual (t) ownership share of responsible institutional investors ownership relative to the total institutional investor ownership at a corporation (f):

$$CA100\ SHARE_{t,f} = \frac{CA100+\ Institutional\ Ownership_{t,f}}{Total\ Institutional\ Ownership_{t,f}} \tag{2.1}$$

where $CA100+\ Institutional\ Ownership_{t,f}$ is the percentage ownership of CA100+ signatories and $Total\ Institutional\ Ownership_{t,f}$ is the percentage ownership of all institutional owners. This specification focuses on the responsible institutional share relative

[8]For more information see: https://www.unpri.org/about-us/about-the-pri

to the arguably active governance share in a firm, i.e. total institutional investors. Figure 2.1 Panel A shows that the proportion of institutional asset under management (AUM) of the CA100+ initiative steadily grew as well as the proportion of PRI signatories and two definitions of IMPACT-PRI investors as robustness measure. In 2022, the average proportion of CA100+ institutional investors at the firm level is 28% (see Table 2.1).

2.2.2 Determining green capital expenditure

Green capital expenditures are a broad concept that the United Nations Environment Programme describes as investments in "infrastructure and assets that allow reduced carbon emissions and pollution, enhanced energy and resource efficiency, and prevention of the loss of biodiversity and ecosystem services".[9] To identify firms' green capital expendiutres, I would ideally like to classify the individual capital expenditures into green and non-green activities. However, corporations do not typically disclose project level capital expenditures.[10] Accetturo, Barboni, Cascarano, Garcia-Appendini, and Tomasi (2022) and Wang, Wurgler, and Zhang (2023) identify green investment components by applying a "green" dictionary to financial statement items for Italian, respectively Chinese firms. De Haas, Martin, Muûls, and Schweiger (2023) use survey responses of managers from European firms to identify green capital expenditures. I approximate green capital expenditures for a worldwide sample by using firms' green debt funding: Financial instruments whose proceeds are directly or indirectly linked to green projects through the contract terms.

Recent financial instruments whose proceeds are either directly or indirectly linked to green projects include (i) green bonds and loans, (ii) sustainability linked bonds and loans, and (iii) sustainability bonds and loans. The proceeds of green bonds are earmarked for environmental projects, sustainability-linked bonds have a coupon pay-

[9] See https://www.unep.org/regions/asia-and-pacific/regional-initiatives/supporting-resource-efficiency/green-economy

[10] The EU now requires large companies to disclose their capital and operating expenditure aligned with the EU taxonomy https://eu-taxonomy.info/info/eu-taxonomy-for-companies

ment linked to key environmental performance indicators and proceeds of sustainability bonds are committed towards environmental or social projects. I define the universe of these instruments as green debt. The first corporate green bond issuance was in 2013[11] and green debt issues can be found in all major SIC divisions (see Appendix Figure A.III). Using green debt as green capital expenditure measure has the advantage of covering a global cross-industry sample for a long time period.

Although green debt neglects investments funded by means other than debt[12], it serves as good indirect measure as it is an important funding source shown to be followed by emission reductions. Total green debt issuance between 2017 and 2022 was 2.3 trillion USD, which accounts for the majority (56%) of global low carbon capital expenditures in this time period.[13] Moreover, 98.7% of green debt in my sample has some form of third party verification, which mitigates greenwashing concerns. Further, Flammer (2021) and Fatica and Panzica (2021) highlight the green investment nature of green bonds by showing that green bond issuers have a better environmental performance post-issuance. I confirm the negative correlation between green debt issuance and emissions in my sample in Appendix Table A.VI. Finally, it is well established that large investment expenditures are financed at least partially with debt, so that the (green) debt financing captures a significant fraction of the green capex (see DeAngelo (2022) for a list of references). Assuming that green debt issuance is approximately proportionate to green capital expenditures, green debt therefore allows me to indirectly measure green investments well over a long time period and across different sectors.

I collect corporate bond and loan data on green bonds and loans, sustainability linked bonds and loans and sustainability bonds and loans from Bloomberg.[14] Between 2013

[11] See SEB Group press release: https://sebgroup.com/press/news/2018/vasakronan-pioneered-green-certificates

[12] There is some suggestive evidence, even though the overall evidence is mixed, of a greenium (e.g. Zerbib, 2019; Baker, Bergstresser, Serafeim, and Wurgler, 2022). To the extent that there is a greenium, firms would have an incentive to issue green debt rather than normal debt to fund green projects. Although outside finance may still be more expensive than internal funds.

[13] BloombergNEF. (2023, January 26). "Global Low-Carbon Energy Technology Investment Surges Past $1 Trillion for the First Time".

[14] I gather all bonds for which one of the following indicators is yes: GREEN_BOND

and 2022 the total number of public green debt issuances is 4,607, of which I am able to match 97% to FactSet via the Legal-Entity Identifier or a ticker/fuzzy name match with manual cross-check. My sample contains 88% of all public issues (93% in terms of amount issued), as shown in Figure A.II. 95% of all green debt instruments are green bonds/ loans and sustainability-linked bonds/loans, whose proceeds are committed or linked to finance environmental and climate-friendly projects. Sustainability bonds/ loans whose proceeds may also be assigned to social projects thus represent only a small fraction. With Bloomberg's comprehensive coverage, my sample is a close map of the universe of public green debt that has been issued over the period of my study.

I construct two main variables $GREENDEBT - DUMMY$, which is equal to one if the firm has issued at least one green debt instrument in a given year and $ASINH(GREENDEBT)$, which is the inverse hyperbolic sine transformation of the dollar amount of proceeds raised through green debt. Table 2.2 Panel B shows that only 0.1% of firms had issued at least one green debt instrument in 2013. Since then, the market has grown multifold, albeit from a very low level. In 2022 2.6% of firms have issued at least one green debt instrument. Asset-weighted, this proportion is an order of magnitude larger and reached 30.7% in 2022. Hence, larger firms are significantly more likely to issue a green debt instrument.

To address the concern that green debt underestimates green capital expenditure, I also look at alternative measures along the value chain. First, I look at the initial research activity of corporations, namely green innovation measured via patent data from Orbis Intellectual Property. Following Bolton, Kacperczyk, and Wiedemann (2022), I use *green patents* which capture technologies that may substitute carbon dioxide emitting technologies for carbon dioxide-free technologies or make carbon-dioxide free technologies more accessible. Given my focus on near-term green outcomes I focus on patent applications. Focusing on applications mitigates the lag between patent grants

_LOAN_INDICATOR; SUSTNABILTY_LINKD_INDCTR; SUSTNBLE_DEBT_INSTRMNT_ INDICATOR; SELF_REPRTD_SUSTAIN_INSTR_INDCTR; SELF_REPRTD_GREEN_INSTR_INDCTR; SELF_REPRT_SUSTAIN_DBT_INSTR_IND; SELF_REPRTD_TRANS_INSTR_INDCTR

and citations (Lerner and Seru, 2022), but may also capture applications that are not evaluated as novel. I further drop the most recent year 2022 in which some applications may have not yet been recorded. My main patent variables are based on the European Patent Office. I use as measures both the patent ratio calculated as the number of green patents over total patent applications (GREENRATIOEP) and a citation weighted count (GREENCITCOUNTEP). Patent ratios relate new patent filings to a firm's innovation capacity and allow a more complete picture of the intensive margin of innovation activity (Bolton, Kacperczyk, and Wiedemann, 2022). The average green ratio (GREENRATIOEP) has risen from 9.6% in 2006 to 14.3% in 2021 for the patenting sample. Patent citation counts scale for the significance of the innovation by the the degree by accounting for the number of citations. As robustness measures, I also consider ratios and citation counts based on patent families at any patent office worldwide and the maximum number of citations of all green patents of a firm in a given year (see Table 2.11).

Second, I collect annual clean revenue and clean investment data from 2019 to 2022 from Corporate Knights. Using their Sustainable Economy Taxonomy (similar to the EU green taxonomy), Corporate Knights calculates the proportion of corporate investment (capital expenditure, R&D and acquisitions) and revenue that is green for about 2,800 companies.[15] While there will be different opinions regarding which activities are green and noise in the classification of activities, this measure captures green investments as well as a measure of the last stage in the value chain, green sales. The average clean investment ratio has increased slightly from 10.1% in 2019 to 14.3% in 2021.

Third, I use S&P Global Trucost to collect data on firm-level scope 1, scope 2 and upstream scope 3 emissions. As a last stage, green capital expenditures should translate into greenhouse gas emission reductions if invested into true green projects. In line with the other green measures, average absolute scope 1 emissions decreased over time (compare Table 2.1 Panel B). However, the sharp drop in average emissions from

[15]See for more detail: https://www.corporateknights.com/sustainable-economy-intelligence/

2015 to 2016 is driven by a substantial data coverage expansion to smaller firms.

2.2.3 Firm financial data

Control variables from firm financial and balance sheet data are from FactSet and include: i) LOGSIZE which stands for the natural logarithm of a listed company's market capitalization (price times shares outstanding); ii) LEVERAGE, which is the ratio of debt to book value of assets; iv) ROE, which is given by the ratio of firm i's net yearly income divided by the value of its equity; v) M/B, which is the end of year market cap divided by the firm's book value; vi) BETA, which is the market beta of individual companies calculated over the preceding 12-month period; vii) VOLAT, which is the standard deviation of returns based on the past 12 monthly returns; viii) momentum, MOM, which is given by the average of the most recent 12 months' returns on stock i, leading up to and including month t-1; ix) short-term reversal, RET, which is the past year's December return on stock i; x) capital expenditure INVEST/A, which we measure as the firm's capital expenditures divided by the book value of its assets. To mitigate the impact of outliers I winsorize M/B, LEVERAGE, INVEST/A, and ROE at the 2.5% level, and MOM and VOLAT at the 0.5% level. Finally, I gather MSCI All Country World Index (ACWI) constituent data from MSCI. I merge the data together using firm ISINs and construct the indicator variable MSCI, which is equal to one if a stock is part of the MSCI ACWI index in year t, and zero otherwise. Table 2.2 highlights that on average 14% of the sample is part of the MSCI ACWI index. The variable definitions are summarized in Appendix Table 2.11.

2.3 Results

2.3.1 Responsible institutional investors & green capital expenditures

2.3.1.1 CA100+ investors and green debt instruments

If the rise in responsible investment movement is reshaping how corporations take into account their environmental impact then we should expect to see a positive relation between green capital expenditures and the share of responsible investors. If, however, this movement is mostly window dressing then we should not expect to see any significant relation (possibly even a negative relation) between green capital expenditures and the share of responsible investors. I first document a strong positive correlation between the CA100+ share and future green debt issuance, which is consistent with responsible investors affecting firms' green capital expenditure decisions.

I formally examine this relationship by estimating the following linear regression model first with year (t), country (c), and 4-digit SIC code industry (j) fixed effects, and subsequently with firm (f) and industry-year (jt) fixed effects:

$$GREENDEBT_{cfjt} = \alpha + \beta CA100\,SHARE_{cfjt-x} + \gamma Controls_{cfjt-x} + FixedEffects + \epsilon_{cfjt} \tag{2.2}$$

The dependent variable $GREENDEBT$ is either the dummy $GREENDEBT - DUMMY$ or $ASINH(GREENDEBT)$, the inverse hyperbolic sine of the amount of green debt raised. The independent variable $CA100\,SHARE$ is lagged by $x = 1, 3$ years. Time-varying firm-level controls $Controls_{cfjt-x}$ measured with with the same lag include LOGSIZE, LOGPEE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. The sample period is defined by the start of the CA100+ initiative and goes from 2017 to 2022.

Table 2.3 shows that both the likelihood of issuing at least one green debt instrument and the amount issued is positively correlated with the proportion of responsible institutional investors over the next year and next three years. Columns 1, 2, 5 and 6 document this positive correlation within industries. In line with Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022); Atta-Darkua, Glossner, Krueger, and Matos (2022); Heath, Macciocchi, Michaely, and Ringgenberg (2021) responsible investors hold greener firms.

In columns 3, 4, 7, and 8, I find that this correlation also holds *within* firm after controlling for firm and industry-year fixed effects. This suggests that responsible investors may not only sort into greener firms, but may also drive firms to become greener. A one standard deviation increase in the CA100+ proportion (22pp) translates on average to a 0.90pp higher probability of issuing a green debt instrument three years later. Considering that on average only 2.6% of firms issued a green debt instrument per year in the sample period, this change represents a 35% increase and is economically large. Importantly, while the R2 increases by about 40%, the size of the coefficient is largely unchanged after adding firm and industry-year fixed effects. This pattern is consistent with limited selection on unobservables(Altonji, Elder, and Taber, 2005). I formally verify this statement and calculate Oster's delta based on the rule of thumb bound of 1.3 times partial R2 (Oster, 2019). This bound assumes that unobservables explain somewhat less than observables. I find that Oster's delta is above 1 which leaves limited scope for unobservables to explain the results. These findings are consistent with the view that responsible investors are influencing firms' green capital expenditure decisions but inconsistent with the alternative view that responsible investors only practice cheap talk.

2.3.1.2 Robustness in the responsible ownership measure

I address over- and under-inclusiveness concerns in identifying responsible investors by considering several alternative responsible share measures, even though classical

measurement error in the independent variable biases the coefficients towards zero and therefore against finding a result. I find that the positive relationship between responsible investors and future green capital expenditures is robust to alternative classifications of responsible institutional investors and specifications of the main regression.

Alternatives to address overinclusiveness To begin with, I focus on the concern that the set of CA100+ signatories is overly inclusive, and limit to a set of plausibly more stringent subsets. Table 2.4 reports in Panel A to D that the positive relationship is robust to the more narrow responsible investor measures that consider only early signatories, drop questionnable institutions and drop high churn or high emission investors. First, in Panel A, I consider only early signatories, i.e. signatories that joined in the first two years (2017 and 2018) of the initiative. I conjecture that late signatories are more likely to be opportunists and be pressured by reputation concerns to join the initiative rather than by true beliefs. Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) show for the PRI initiative that late joiners have worse total portfolio ESG scores. Second, in Panel B, I adjust the CA100+ signatory base and drop the two large passive investor signatories, BlackRock and State Street Global Advisors. They offer passive index offerings and the degree to which they are active owners is often challenged.

Third, I adjust my "self-declaration"-based responsible investor measure by accounting for portfolio-inferred types and preferences.[16] Specifically, I follow Gaspar, Massa, and Matos (2005) to calculate the quarterly investor churn rate and group investors in annualized terciles. I define investors in the top tercile, i.e. those with the highest churn rate, to be short-term investors and remove any institutional investor that appeared at least once in the top tercile between 2017 and 2021, the period of interest. This mixes the two primary methods of identifying responsible investors, i.e. self-

[16]The identification of short-term and high emission investors is at the reporting institution level, which is often below the global parent level. BlackRock for instance has more than 40 reporting institutions. This adjustment thus also allows me to abstract from the stark one-zero classification at the aggregate institutional investors and lower it to the reporting institution level.

declaration and revealed preferences, and therefore may allow me to more cleanly identify the truly long-term responsible investors. Panel C documents that the positive relationship if anything is slightly stronger after removing long-term signatories. Fourth, I similarly identify and drop investors with the highest portfolio weighted absolute scope 1 emissions. I calculate total portfolio weighted scope 1 emissions in line with Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022). I require at least 50% of an institutional investors portfolio to have emission data and calculate the portfolio weighted score of the most recent 8 quarters. I sort investors into portfolio weighted terciles and define the top tercile with the highest emissions as high emission investors. Investors without an emission score are considered to be part of the highest emission tercile. I again remove any institutional investor that has been identified at least once as high emission investor between 2017 and 2021. Panel D again confirms the positive relationship.

In Appendix Table A.VII, I additionally show that the results are robust to the "participant" signatory subset, which are the institutional investors who are actively involved in firm engagements, and excluding high emission investors identified based on scope 1 emission intensities rather than absolute emissions. Finally in Appendix Table A.VIII, I randomly sort signatories into 5 buckets and iteratively calculate the responsible investor share based on 4 out of the 5 buckets and show that the results are not driven by a specific group of signatories. Across the different specifications, the size of the coefficient remains relatively stable and significant. My findings therefore do not seem to be driven by a specific signatory or a set of institutional investors whose sustainable preferences can be challenged.

Alternatives to address underinclusiveness Alternatively, my responsible investor measure may also miss out on important responsible investors who are not part of the initiatives and actually be under-inclusive. I construct an alternative measures for responsible ownership based on the older and larger PRI initiative instead of the CA100+ initiative. PRI is a leading global network of financial institutions that com-

mit to incorporate environmental, social and governance issues in their investment analysis and ownership practices. While it is one of the largest sustainable investor initiatives with $121.3 trillion AUM in 2021, its size and weaker membership requirements have also generated doubts about the "true responsibility" of these investors (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022). I therefore use the PRI survey responses from the PRI reporting framework to filter for institutional investors in this subset that similar to CA100+ follow an engagement strategy and are therefore more likely to actively care about global decarbonization. I call these "IMPACT-PRI" investors and describe the steps taken in detail in Appendix Section A.1.3. The variable $IMPACT-PRI\,SHARE$ is calculated as the $CA100\,SHARE$ in equation 2.1. In Table 2.4, Panel E, I report results with IMPACT-PRI SHARE as independent variable and again identify a significant positive relationship with future green debt issuance. Because of the earlier start period, this variable is available from the first green bond issuance in 2013 onwards. Given that the PRI-based responsible investor measure is likely much noisier, it is unsurprising that the size of the coefficient is smaller. However, the relationship between responsible ownership and green capital expenditures is still positive and significant. In Appendix Table A.VII, Panel C, I show the results are also robust to a broader CA100 SHARE measure, which considers the Norges Bank Investment Management (NBIM) as a signatory from the start of the CA100+ initiative. NBIM is often considered to be an active climate steward, but is not part of the initiative.

Alternative specifications In my main specification, I scale responsible institutional ownership relative to total institutional ownership to focus on the fraction of investors that are arguably actively involved in firms' governance. This scaling treats firms with little institutional ownership similar to firms with large institutional ownership and raises concerns that the results are driven by firm observations with little institutional ownership. I next show that the results are robust to various alternative regression specifications that account for total institutional ownership.

I first restrict the sample to firm-years with at least 10% institutional ownership and confirm that the results are not driven by firms with very little institutional ownership in Panel A of Appendix Table A.IX. Next, I consider an alternative specification with responsible institutional ownership measured relative to total ownership and an additional control for total institutional ownership to address the concern that institutional investors select into certain firms. This idea follows Hong and Kacperczyk (2009) who control for firms in industries related to sin stocks. Appendix Table A.IX, Panel B, highlights that responsible ownership is again positively related to green debt issuance. The results further suggest that institutional ownership in general is negatively related to green debt issuance. If firms' green investments are relatively lower NPV projects, it makes sense that institutional investors in general would drive managers to shun away from these projects. Finally, in Panel C of Appendix Table A.IX, I replace CA100 SHARE with indicators for different levels of CA100 proportion. The positive relationship is confirmed, as the dummy for 30%+ responsible ownership is statistically significantly positive and larger than the dummy for responsible ownership between 10% and 30%.

2.3.1.3 Robustness in the green capital expenditure measure

I cannot measure green capital expenditures directly and instead approximate it with green debt. As proxy, green debt is possibly under-inclusive and at worst biased. I document that the positive relationship between responsible investors and green capital expenditures is robust to alternative green debt definitions, taxonomy-based revenue and investment ratios, green innovation and emissions. Across many different green capital expenditure proxies, I find results in line with the view that responsible investors pressure corporations to reduce their environment impact. These results support the conjecture that green debt is a good proxy of green capital expenditures and further alleviate concerns that green debt is uncorrelated to green capital expenditures.

I start by confirming that the positive relationship between responsible investor shares and green debt also holds for subsets of the green debt universe, specifically externally verified green bonds/ loans and externally verified sustainability-linked bonds/ loans. External verification of the bonds remedies the concern that the proceeds do not actually end up in green projects. Further, green bonds/ loans target environmental projects only rather than the mix of environmental and social projects for sustainability bonds/ loans. Sustainability linked bonds/ loans do not earmark proceeds to specific projects, but link the borrower's financing costs to key environmental performance indicators. They thus allow to capture green capital expenditure from firms that are unable to tie proceeds to a specific project. Appendix Table A.X shows that the responsible investor share also correlates positively with the future issuance of these debt instruments both within industry and firm.

Flammer (2021) points out that a large fraction of green debt instruments are issued by financial institutions, whose incentives and use-of-proceeds may differ from non-financial institutions. I confirm this pattern in my data in Appendix Figure A.III Panel B. To ensure that my results are not driven by this subset, I repeat the main specifications and drop all financial institutions. Appendix Table A.XI shows that the results are robust to dropping this subset.

Next, I repeat the main specification with the alternative green capital expenditure proxies and confirm that the relationship also holds for the other measures although with a different degree of significance. A first alternative measure of green capital expenditures is to classify firms' total capital expenditures into green and non-green. Corporate Knights' Sustainability Economy Taxonomy aims to do so. I rerun specification 2.2 with Corporate Knights $CLEANREVENUERATIO$ and $CLEANINVESTMENTRATIO$ as dependent variable. I find a significant positive correlation with country, industry and year fixed effects, as shown in Table 2.5 in Panel A. The results with firm and industry-year fixed effects are insignificant, but for the $CLEANINVESTMENTRATIO$ align qualitatively with the baseline specification.

A second alternative measure of green capital expenditures is to look at green activities. I therefore measure corporate level green innovation with patent data from Orbis Intellectual Property. Given the count (count-like) data of the patent variables, I estimate specification 2.2 with a Pseudo Poisson Maximum Likelihood model. Table 2.5, Panel B, shows that the correlation between the CA100 SHARE and future green innovation measured with the patent ratio ($GREENRATIOEP$) or citation count ($GREENCITCOUNTEP$) is positive and significant in most specifications. In Appendix Table A.XII, I consider alternative patent activity measures incorporating patent activity at worldwide patent office, that are less stringent than the European Patent Office, in Panel A as well maximum citations as alternative innovation measure in Panel B. These measures also broadly confirm the positive relationship.

Finally, I consider greenhouse gas emissions as third alternative measure, that looks at the outcome of green capital expenditure. Firms' emissions as ultimate end-goal are of particular interest. Table 2.5 Panel C and D consider as dependent variables log absolute scope 1 emissions ($LOGS1TOT$) and scope 1 emission intensity based on firm level revenues ($S1INT$), respectively scope 2 absolute ($LOGS2TOT$) and intensity ($S2INT$) metrics. I find a statistically negative coefficient for the one and the three year-lagged CA100 SHARE coefficient across most specifications with firm and industry-year fixed effects. In Appendix Table A.XIII, I also consider upstream scope 3 emissions. Here, the results are mostly statistically insignificant suggesting the the responsible investor pressure may not stretch beyond the target firm to the suppliers for the given time period. In general, the results suggest that there are real firm-level changes and strides towards net-zero following responsible investor pressure.

2.3.2 Cross-listing in the United States as negative responsible ownership shock

2.3.2.1 Hypothesis and methodology of the cross-listing "shock"

To isolate the causal impact of responsible investors, I exploit variation in the firm-level share of responsible institutional investors induced from European and Asian firms cross-listing in the United States. The positive correlation between responsible ownership and green capital expenditures may be driven by omitted variables, for instance, certain firm characteristics that may jointly affect ownership and firm behavior. Even though I control for firm and industry-year fixed effects as well as various firm level controls, there may still be bias. Further, there may be reverse causality. Responsible institutional investors may sort into firms with higher planned green capital expenditures rather than driving green capital expenditures. I address these concerns by exploiting variation in responsible ownership driven from firms cross-listing in the United States, i.e. opening a secondary listing in the United States next to their home listing either with or without a capital raise. I estimate the results with a staggered difference-in-differences estimation with matching.

Regional difference in institutional investor sustainability is the key source of variation. The proportion of institutional investors with a sustainable investment orientation in Asia and Europe is on average substantially higher than in the United States (GSIA, 2021; Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022). Figure 2.1 Panel B, documents this for the CA100+ initiative, where the 2017 to 2021 average Asian and European proportion of institutional AUM signed up to the CA100+ initiative is more than 20% above the American proportion. Moreover, Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) suggest that American institutional investors that commit to a sustainable investment initiative, the Principles for Responsible Investment initiative, are on average less likely to follow up on this commitment because of commercial motives, uncertainty about fiduciary duties and a less mature

ESG market. Based on these observations, I propose that cross-listing in the United States should increase the proportion of American investors and therefore decrease the proportion of responsible institutional investors within a firm.

While cross-listing may create variation in responsible institutional ownership, the decision to list in the United States is an endogenous decision a firm takes. Cross-listing in the United States may not only change American institutional ownership, but also affect firms on different dimensions. My identifying assumption is that a firm's decision to cross-list does not affect nor reflect relative green investment opportunities other than through the impact on the proportion of responsible institutional investors. I first assess this assumption qualitatively by studying managers' stated motivation for cross-listing and the theoretical literature on why firms cross-list.

Common motivations cited by corporate managers that have successfully executed cross-listing include access to a larger and deeper market for capital, enhanced visibility, diversification of their investor base, and greater liquidity of their stock (Bancel and Mittoo, 2001, 2009; Fanto and Karmel, 1997; Mittoo, 1992). I manually inspect annual reports and press releases for half of my cross-listing sample and find that this echoes the reason stated in these public reports. Appendix Table A.II summarizes my results. In line with the literature survey results, my findings highlight the importance of access to capital and visibility in the cross-listing decision. The main theoretical reasons put forward for firms' cross-listing include the "market segmentation hypothesis", "bonding hypothesis", and "insulation hypothesis" (see Appendix Section A.2.1 for a detailed discussion on why firms cross-list). The arguments focus on how accessing other markets and improving firms' governance can lower cross-listings firms' cost of capital, but are orthogonal to sustainability reasons. Both, managers' stated motivations and the theoretical literature on cross-listing suggest that the decision to cross-list in the United States is unlikely to be driven by firms' desire to reduce the proportion of responsible investors. Further, I show in Appendix Section A.2.1.1 that an increase in responsible ownership is not associated with more cross-listings at the country, industry or firm level.

I collect data on cross-listings in the United States using the share codes 12, 30 and 31 from CRSP.[17] I merge this data using ISINs and focus on cross-listings from firms with their headquarter in Asia or Europe. I require the treated firms to have at least 3 years of financial controls and ownership data (one year before to one year after the cross-listing year). My final sample includes 96 firms (31 Asian firms and 65 European firms) that cross-list between 2007 and 2021. Figure 2.2 shows that the treatment is staggered over multiple years with at least two treated firms per year and up to twelve treated firms in a given year. The staggered adoption and involvement of different industries and countries mitigates concerns that the results are driven by specific time trends affecting particular groups of firms.

To choose the control group, I first calculate propensity scores based on the ex ante (1 year before inclusion) characteristics LOGSIZE, INVEST/A, ROE and LEVERAGE and region and 2-digit SIC fixed effects. I then perform exact matching on the region (Asia or Europe) and 2-digit SIC industry and choose the three nearest neighbors based on the propensity score with replacement. Table 2.6 shows the quality of the matching for the four match variables as well as for American share, responsible investor share and green capital expenditures over the four years prior to cross-listing. While the American share and emissions are at a different level before cross-listing, one-year changes as well as the level of the CA100+ share and green debt issues are not statistically different for the treated group from the control group. The balance table thus suggests that treated and control firms are not on a different trend before cross-listing.

I follow Sun and Abraham (2021b) to estimate the staggered difference-in-differences that restricts the control group to never-treated observations. In the staggered difference-in-differences estimation with only lead and lags already treated units act as controls for newly treated units and weights across treatment cohorts may be non-intuitive or at worst negative (Goodman-Bacon, 2021; Roth, Sant'Anna, Bilinski, and Poe, 2023). I estimate cohort-specific average treatment effects on the treated

[17] Share code 12 refers to ordinary common shares from firms incorporated outside the United States and share codes 30 and 31 denote American Depository Receipts (ADRs) covering Level II and III ADRs (see also Chaplinsky and Ramchand (2012)).

($(CATT(e,\ell))$), ℓ periods from initial treatment for cohort first treated at time e. I subsequently calculate the interaction-weighted estimator by aggregating the cohort-specific coefficients for each relative time period based on the given sample share in that period (Sun and Abraham, 2021b). I use the maximum available time span for each variable in the estimation. While I can only measure the proportion of CA100+ investors over a short-time period, I conjecture that American investors have been less sustainability oriented on average beforehand already. Cross-listing in the United States should therefore tilt the institutional investor base towards a lower sustainable orientation across the different time periods.

$$y_{ft} = \alpha + \sum_{e \in \{2007,2008,\ldots,2021\}} \sum_{l=-15,\neq -1}^{15} \delta_{e,l} \mathbf{1}\{E_f = e\} RP_{ft}^{\ell} + \gamma Controls_{ft-1} + \theta_f + \tau_t + \epsilon_{ft} \tag{2.3}$$

The dependent variable is a firm-year measure of American ownership or responsible ownership (CA100 SHARE or IMPACT-PRI SHARE) for the first step of my hypothesis and GREENDEBT-DUMMY or ASINH(GREENDEBT) in the second step. RP_{ft}^{ℓ} are relative period indicators that are equal to one for a firm calendar year observation, where the time relative to the cross-listing year matches the dummy statement and zero otherwise. For instance, the relative time period dummy minus 2, RP_{ft}^{-2}, is equal to one for any firm in calendar year 2018 that listed in the United States in 2020. To avoid multicollinearity I drop the relative time period dummy "minus 1". $\mathbf{1}\{E_f = e\}$ are cohort specific indicators for firms in a given cross-listing year. For instance the cohort dummy "listing year" 2020 ($\mathbf{1}\{E_f = 2020\}$) is equal to one for firms that listed in the United States in 2020. I additionally include firm level controls as before.

I first assess the plausibility of the parallel trend assumption in Figure 2.3 and Figure 2.4 and visually inspect the data around the listing period. Firms listed between the years -1 and 0. I do not observe any clear differential pre-trends in both ownership dependent variables and green capital expenditure proxies between the two groups of firms. Yet, Roth (2022) highlights that this visual pretest inspection may fail to detect pre-existing trends that can produce meaningful bias in the treatment effect. I follow

Roth (2022) to identify whether my pre-test is likely to be well powered against violations of parallel trends. I plot a linear violation in Appendix Figures A.IV and A.V with a hypothesized slope based on having 50% power, i.e. the probability of passing the pre-test is 50%. The estimated slopes are economically meaningful, e.g. a 1.6pp annual increase in the US share translates into a hypothesized difference of 4.8pp three years later relative to a 30% average share in the US share. Similarly, a negative 0.3pp slope for green debt instruments translates into a 0.9pp difference three years later relative to a 2% average in green debt issuance. The likelihood ratio for this hypothesized trends are displayed in Appendix Table A.XIV and are between 0.02 and 1.6, i.e. the chance of seeing the observed pre-test coefficients under the hypothesized trend relative to under parallel trends is at most 60% higher but often less likely. This observation supports the plausibility of the parallel trend assumption and the qualitative evidence that the reason for cross-listing is unrelated to managing firms' responsible ownership.

2.3.2.2 Impact of cross-listing on ownership and green capital expenditure

I first document the increase in American institutional ownership and decrease in responsible ownership post-cross listing. Following the cross-listing, the share of American institutional investors is on average 8.8pp higher for the treated firms relative to the control group three years post cross-listing. Further, the CA100 SHARE (IMPACT-PRI SHARE) decreases on average by 5.1pp (6.0pp) three years post cross-listing. While the CA100 SHARE for instance is only available for a short period, the IMPACT-PRI SHARE, as an alternative measure of responsible institutional investor ownership with a longer time series, also highlights a pronounced drop in the responsible investor share. This supports the decision to measure the impact on green debt over the maximum time period available, i.e. starting with firms first cross-listing in 2014 to have at least one year of pre-treatment data available.

The correlation results suggest that lower responsible ownership may translate into

lower green capital expenditures. I next assess whether the plausibly exogenous decrease in responsible ownership post cross-listing also translates into lower green capital expenditures. Figure 2.4 shows that the probability of firms issuing at least one green debt instrument decreases by 4.6pp three years after the treatment[18]. Panel B and C in Figure 2.4 highlight that the amount green debt raised decreases post cross-listing and absolute scope 1 emissions increase post cross-listing. I also document an increase in scope 1 emission intensities in Appendix Figure A.VII and a decrease in green innovation in Appendix Figure A.VIII. Emission and green innovation as alternative measure mitigate any concern that green debt as a capital source is impacted by the cross-listing for reasons unrelated to responsible investor pressure. Together, the results are in line with the view that lower responsible ownership leads to lower green capital expenditures.

Concerns in the identification approach include a general change in investing post cross-listing, governance differences in particular between the United States and Asia and more generally some unobserved variable or shock driving cross-listing and decreases in green debt. Despite matching firms on capital expenditure relative to assets, firms cross-listing in the United States may have different (more) investment opportunities than firms that do not cross-list. Yet, listing in the United States should increase access to capital and is usually expected to increase capital expenditures. If green capital expenditure stays proportionally to general capital expenditure, I would have expected green capital expenditure to increase. I find that green debt instruments issuance drops. Part of the initial drop in green debt instruments may be explained from a more general decrease in debt funding need following new raised capital from the cross-listing. However, I find a long pronounced drop in green debt issuance that persists four years after listing in the United States. Indeed, when I look at capital expenditures and total outstanding long-term debt in general in Figure 2.5, I do not find any statistically significant change between firms that cross-list in the United States

[18]In Appendix Figure A.VI, I show the Bacon decomposition for all possible two-group/ two-period DID estimators of the general two-way fixed estimator (Goodman-Bacon, 2021). This figure shows the "good" Treated vs Never-Treated estimates are all negative and would account for 85% of the general two-way fixed effect estimator.

and those that do not. Furthermore, in Appendix Figure A.IX I also show that the proportion of foreign sales do not increase significantly post cross-listing. This alleviates concerns that firms' business model changes radically post cross-listing.

In Asia, the average institutional ownership and the regulatory environment is more different from the United States relative to the difference between Europe and the United States. Both differences may imply that more factors may convolute the cross-listing of Asian firms. I therefore repeat the analysis with European firms' cross-listings only. Results in Appendix Figures A.X and A.XI show that the reduction in responsible ownership and green capital expenditure also hold for the European only sample.

Lastly, I also consider the flip side of European and Asian firms cross-listing in the United States, namely American firms' cross-listing in Europe. While the firm rationale and its characteristic may differ substantially for different cross-listing destinations (see e.g. Pagano, Röell, and Zechner (2002)), American firms' cross-listing on European exchanges should increase their exposure to European investors, who are on average more sustainable. I therefore expect their share of responsible investors and the green debt issuance to increase. I collect the ticker, exchange, currency of the ticker and date of all public firms cross-listing on a European exchange from SP Capital IQ for the total available time series.[19] This approach includes securities listed on exchanges as well as over the counter listings.[20] More than 90% of the cross-listings I identify are over-the-counter cross-listings, which weakens the expected shareholder structure impact. Yet, after matching the 143 American firms that cross-listed in Europe (see Appendix Figure A.XII) following the same approach to the three nearest neighbors, I still find a small positive increase in the responsible share and (insignificant) increase in green debt issuance.

[19] Chen, Ng, and Tsang (2015) highlight that collecting cross-listings through SP Capital IQ provides a more complete picture of foreign firms' cross-listings than relying on data from major stock exchanges that on top of this have varying definitions of foreign firms.

[20] The first cross-listing is an over-the counter listing by Host Hotels & Resorts, Inc. in 1953 on Deutsche Boerse

Together, my findings support that responsible institutional investors drive firms to increase green capital expenditures and contradict the view that responsible investors only engage in cheap talk.

2.3.3 Evidence for responsible investor engagement

Responsible investing can affect firms' green capital expenditures through two main channels. First, a larger sustainable investment sector lowers cost of capital for green projects and therefore incentivizes management to invest in green projects (e.g. Heinkel, Kraus, and Zechner, 2001; Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2021). Second, responsible institutional investors can exert influence over firms' capital expenditure by voicing their preferences, i.e. by engaging with management (e.g. Broccardo, Hart, and Zingales, 2022; Biais and Landier, 2022; Chowdhry, Davies, and Waters, 2019; Oehmke and Opp, 2022). They can push the implementation of internal governance mechanisms that set incentives in line with their preferences and ultimately drive management to act in line with their preferences. Dimson, Karakaş, and Li (2015) show empirically that engagement is an effective tool in influencing corporate decisions. In Appendix Section A.5, I expand the model by Pástor, Stambaugh, and Taylor (2021) and show that inducing shareholder preferences for green technologies on management through social impact linked compensation increases firms' green capital expenditure above any pure green asset demand side effects. Oehmke and Opp (2022) more formally study optimal engagement via a contracting approach. Sustainable investors with a real impact mandate are willing to accept lower rate of returns in return for control over the technology the company adopts. These observations motivate that investor engagement with management is an important channel for investors to accelerate green capital expenditure. In line with this, one of the distinguishing characteristics of the CA100+ initiative is its engagement strategy to drive firms to reduce their greenhouse gas emissions. I therefore hypothesize that responsible investors engage with their portfolio companies to achieve their

desired objective of lower carbon emissions. I expect to see higher number of engagements and the implementation of appropriate internal governance mechanisms.

I start by documenting that within the PRI survey subset, CA100+ investors engage more with management on environmental, social and governance topics than non-CA100+ investors. The histogram in Figure 2.6 shows that the distribution of engagement by non-CA100+ investors is right-skewed with more than 55% of non-CA100+ investor-year observations having less than 100 engagements per year. In contrast, less than 18% of CA100+ investor-year observations have less than 100 engagements per year. In general, the distribution of CA100+ investor-years has substantially more mass shifted towards a higher number of annual engagements.

Next, I observe that responsible ownership is associated with tighter future environmental governance that monitors and incentivizes management to invest in green technology. A first commitment device is a decarbonization target. Decarbonization targets may self-discipline management and ensure that the advertised carbon emission reductions are carried out. Bolton and Kacperczyk (2023a) point out that these commitments are associated with future decarbonization and are mostly set by already low greenhouse gas emitting firms or firms willing to reduce greenhouse gas emissions. To push firms to commit to the green transition and track their progress, responsible institutional investors should drive firms to set decarbonization targets. The Science-Based Targets initiative (SBTi) enables organizations to set science-based emissions reduction targets. I construct two indicator variables identifying SBTi signatories (SBTSIGN) and SBTi target setters (SBTTGT). SBTSIGN is one for firms that commit to set a decabronization target or have already set a decarbonization target and zero otherwise. SBTTGT is one for firms that have set and got an approved decarbonization target. I use SBTSIGN and SBTTGT as dependent variable in the main specificatoin 2.2 with firm and industry-year fixed effects. Table 2.7, Panel A, highlights that a higher responsible investor share is followed by being more likely to be a signatory and have an approved target. I also repeat this analysis with the cross-listing sample. Figure 2.7 shows that European and Asian firms probability of becoming a

SBTi signatory decreases post cross-listing, i.e. after the responsible ownership drop. This result suggests that responsible institutional investors may be causally related to stricter environmental governance.

Environmental responsibilities and incentives at the executive level are another environmental governance tool to direct management strategy. Using Refinitiv ESG data, I construct indicator variables for firms having a chief sustainability officer (CSO), sustainability responsibilities assigned to at least one executive (EXECSUSRESP) and sustainability targets in executive compensation (EXECSUSCOMP).[21] Following Strand (2013), I first screen managers' job titles for the words "sustainable", "sustainability", "responsibility", "ethics", "environment", "climate", "CSO", "CSR" and subsequently manually scrutinize the job title to identify CSOs. I rerun specification 2.2 with the environmental governance variables as dependent variables and firm and industry-year fixed effects. Table 2.7, Panel B, shows that there is a positive association between the responsible investor share and future environmental executive responsibilities. A one standard deviation increase in the CA100 proportion (0.22), translates on average in a 1.2pp higher probability of having a CSO, a 2.1pp higher probability of executive responsibility for sustainability issues and a 1.1pp higher probability of sustainability targets in executive compensation three years later. Higher proportions of responsible institutional investors thus correlate with stronger future firm-level environmental governance that creates incentive structures to spur green capital expenditure.

Finally, given that engagement with firms is costly for institutional investors, institutional investors should concentrate their effort on the most important firm subset for the net zero transition. Indeed, the CA100+ initiative initially only targeted the 100 highest emitters and has subsequently expanded its focus now targeting 171 companies that it believes play a critical role in the net zero transition. I define $CA100\ TARGET$ as a time-varying dummy equal to one if the firm is part of the target companies of the CA100+ initiative. Using Trucost emission data, I also create a

[21] I use the variables CG_BD_CP_DP039: Senior Executive CSR Sustainability Compensation Incentives and CG_BD_CP_DP029: Senior Executive Responsibility for CSR Sustainability to identify if at least one senior executive has sustainability responsibilities respectively compensation incentives

dummy ($HIGHEST\ EMITTERS$) equal to one for the 200 companies with the highest scope 1 emissions in 2016, which is the year before the CA100+ initiative was launched. The 200 highest emitters are responsible for more than 70% of total scope 1 emissions in my sample in 2016 and their decarbonization is thus critical for the net zero transition. Already green companies have limited scope to reduce emissions further. Institutional investors whose goal is the net zero transition should therefore focus their attention on the highest emitters subset.

Similar to the main specification 2.2, I run the pooled regression specification 2.4 with the interaction term, firm fixed effects and industry-year fixed effects. The coefficient of interest is β_2, which captures interaction between the $CA100\ SHARE$ variable and either $TARGET$ group. While $CA100\ TARGET$ is time-varying, $HIGHEST\ EMITTERS$ is constant and β_3 is therefore not estimtaed with $HIGHEST\ EMITTERS$ as $TARGET$ group.

$$GREENDEBT_{fjt} = \alpha + \beta_1 CA100\ SHARE_{fjt-x} + \beta_2 CA100\ SHARE_{fjt-x} * TARGET_{fjt-x} + \beta_3 TARGET_{fjt-x} + \gamma Controls_{cfjt-x} + \theta_f + \tau_{jt} + \epsilon_{fjt} \tag{2.4}$$

If institutional investors target a certain subset, the correlation between responsible ownership and green capital expenditure should be stronger for this subset. Table 2.8, Panel A, reports that the correlation with future green capital expenditure is indeed multiple magnitudes stronger for these subsets. A one standard deviation increase in the CA100 SHARE (22pp), translates on average in a 11.44pp higher probability of issuing green debt three years later for the the highest emitters. In contrast, for the rest it only leads on average to a 0.84pp higher probability of issuing green debt three years later. Part of the economically much larger effect is explained by unconditional green debt issuance being substantially higher for the highest emitters (see Appendix Figure A.XIV). On average, 19.00% of the highest emitters issued green debt in the sample period compared to 2.45% for the remaining sample. Yet, the percentage change is still

larger for the highest emitters (60% vs 34%) suggesting that some of the effect is driven by stronger responsible investor pressure for this subset. In line with this result, I also find that the effect on absolute and emission intensity scope 1 emissions are stronger for the highest emitter and CA100+ target subset (compare Appendix Table A.XV.

I repeat this exercise with the environmental governance variables, as I also expect that environmental governance is more stringently implemented within the highest emitters. Panels B and C of Table 2.8 show that the interaction terms are mostly positive and significant for both decarbonization targets and executive environmental responsibilities. The effects are strongest for the largest emitters on which responsible institutional investors are most likely to focus on if they want to achieve impact. Overall, these results suggest that responsible institutional investors engage with firms to change their behavior. While it does not pin down the mechanism to engagement, engagement likely plays an important role in how responsible institutional investors drive firms to increase green capital expenditure.

2.3.4 Factors moderating responsible investors' pressure

Responsible institutional investors are not operating in isolation, but are one factor of many in the net zero transition. Given the plurality of net zero transition pressures, this section aims to understand for which firms responsible investor pressure bites most and under which circumstance responsible institutional investors are most active. My results suggest that responsible investor pressure is more effective in firms with more resources to respond and in environments where other net-zero transition pressure exists.

My first hypothesis is that larger and more profitable firms have the necessary resources to respond, while smaller and less profitable firms are more constrained and less able to enter into lower net present value projects. To test this hypothesis, I interact the responsible investor share (CA100 SHARE) with LOGSIZE and ROE. Table 2.9 reports the results and documents that the interaction terms are positive and sta-

tistically significant. In line with the hypothesis, responsible investor pressure is more impactful for larger and more profitable firms.

I next assess how responsible investor pressure interacts with other societal net zero transition pressure. As environmental regulation and other societal pressure to reduce emission tighten, green business models become more profitable. Responsible investors may act as substitute or complement to other societal pressures. If other net zero transition incentives are sufficient or other pressures weaken responsible investors' perceived necessity for action, they may operate as substitute. On the other hand, stronger other net zero transition incentives may strengthen responsible investors' position and ambition. Ex-ante more profitable green business models should ease negotiation with management and other shareholders to push green projects and can thus accelerate responsible investor action.

I collect data on six different measures of net-zero pressures covering dimensions from regulatory to broader consumer pressures. First, I construct a time trend (TIME), as societal awareness and pressure has been increasing over time. Second, I interact the CA100 SHARE with the firm headquarter regions. The political and societal pressure to speed up the energy transition differs across regions and is probably strongest in Europe. Europe for instance introduced the the world's first major carbon market and it remains the biggest one.[22] Third, I include three measures of regulatory pressure. The regulatory measures include country level net environmental taxes (NETENVAXES) and measures of normalized domestic (DOMPOLICY) and international policy (INTPOLICY) tightness follwoing Bolton and Kacperczyk (2023b). I collect country level data on environmental taxes and fossil fuel subsidies from IMF[23] and define net environmental taxes as the difference of environmental taxes relative to GDP and fossil fuel subsidies relative to GDP. Countries with higher net environmental taxes should provide a more feasible business environment for low emission technologies. Germanwatch calculates annual country level domestic and international climate change pol-

[22] EU Emission Trading Scheme
[23] IMF Government Policy Indicators

icy tightness based on domestic regulation and international pan-governmental agreements. Fourth, I use a more consumer pressure related measure (NGO-CAMPAIGN), which captures an increase in NGO campaign pressure faced by a corporation. Sigwatch tracks firm-level NGO campaign events, which can be a new target or country for pressure, a new allegation, a report or significant public protest (Hatte and Koenig, 2017). I count the number of climate change campaigns a company faces in a given year and construct a dummy equal to one if the number of campaigns a firm is exposed to increased relative to the last year. The dummy is equal to zero for firms where the number of campaigns decreased, remained flat or are not covered.

The results in Table 2.10 are consistent with the view that responsible investor pressure is complementary to other societal pressures rather than a substitute. The time trend interaction is positive and statistically significant. Further, the responsible investor pressure is strongest in Europe, which has been more active in addressing the energy transition. Similarly, the interaction with the regulatory pressure variables is positive and mostly significant. Lastly, the interaction with the NGO-CAMPAIGN dummy is also positive, which suggests that the investor pressure may have been more effective in years where the number of campaigns a company has faced increased. All interactions point towards a complementarity between responsible investor pressure and net zero transition pressure. The complementarity suggests that responsible institutional investors pressure alone may be insufficient. Rather, it is the combination with other net zero transition pressures that leads to a strong acceleration of green capital expenditure.

2.3.5 Responsible investors and green capital expenditures' role in decarbonization

My results suggest that responsible ownership has an economically meaningful impact on a firm's green capital expenditure, but does this effect also aggregate to an economically meaningful quantity at the global level? To assess this question, I first quan-

tify the global impact of responsible investors on green capital expenditures. Next, I compare the pressure of responsible investors to the impact of a carbon tax. Lastly, I provide some suggestion of the importance of green capital expenditure in emission reduction relative to the sale of high emission-intensive assets. Although estimating aggregate economic effects using my empirical exercise is challenging in the absence of a general equilibrium model, I provide back of the envelope calculations for aggregate economic implications abstracting from general equilibrium considerations to be able to judge the relative importance of responsible institutional investors. My results suggest that responsible investors' global impact is similar or greater than the effect of a carbon tax. While responsible investors as capital source and governing agent represent an important force, to limit warming to 1.5°C multiple tools may be needed.

I first translate my results into a measure of the aggregate impact on green capital expenditures. I focus on the correlation results, as these cover the global sample and are therefore likely more representative than the smaller cross-listing sample. A one standard deviation increase in the CA100+ share (22pp) is associated with a 0.041pp higher probability of issuing green debt. Between 2017 and 2021, the average proceeds from a green debt issuance were $350 million in my sample. There are currently about 60,000 public firms.[24] Assuming that the responsible investor share increases across all public firms by one standard deviation, this change would translate into about $200 billion additional green debt.[25] This increase represents about 20% of current green capital expenditures (about $1 trillion in 2022). Although the effect is relatively large compared to current levels, it is still insufficient to close the current $3 trillion gap to be on a net zero trajectory.

I next compare the impact of responsible investor pressure to a carbon tax. Green (2021) assesses 37 studies on carbon taxes and finds that the aggregate reductions from carbon pricing on emissions are limited and translate only into 0% to 2% lower emissions per year. I find that a one standard deviation increase in responsible ownership

[24] World Federation of Exchanges. (2022 May). "Number of Listed Companies".
[25] $\$350mn * 60,000 * 0.22 * 0.041 \approx \$189bn$

(22pp) translates over three years into a 3.6% reduction in emissions across all firms worldwide (see Table 2.5), equivalent to 1.2% annually. Considering that the European Union Emission Trading Scheme and other carbon taxes typically target manufacturing installations and are thus tilted towards high emission firms, a more accurate comparison group may be the impact on the highest emission subset. For the largest 200 firms, I find on average a 13.2% reduction over three years for a one standard deviation increase in responsible ownership (see Table A.XV), equivalent to 4.4% annually. My calculations therefore suggest that a one standard deviation increase in responsible ownership is associated with a 1.2% to 4.4% decrease in annual emission reductions. This magnitude is similar and possibly even greater than the impact of a carbon tax on emissions (0% to 2% annual emission decrease). However, the required decarbonization rate to limit warming to 1.5° is about 8% per annum until 2030 .[26] Therefore responsible investor pressure seems to be one economically important driver and within a set of multiple tools can contribute to achieve the necessary decarbonization rate to limit warming to 1.5°C.

Lastly, how much of the reduction in emissions may be attributed to green capital expenditures and changes in operations versus the sale of brown assets. To shed some light on this matter, I compare the change in emissions to changes in assets and sales as well as changes in emission intensities. Table 2.5, Panel C, shows that higher responsible ownership is not only followed by a decrease in absolute scope 1 emissions, but also scope 1 intensities. This result suggests that firms invest to improve the efficiency of their existing operations, respectively in greener operations. Further, I document in Appendix Table A.XVI Panel A that a higher share of responsible ownership is also associated with a statistically significant decrease in assets and sales, but the coefficients are only about half the size of the change in total scope 1 emissions (0.08 vs 0.17 compare Table 2.5). It is therefore unlikely that all emission reduction is driven by the sale of brown assets. Moreover, for the highest emitter subset, sales may even increase, al-

[26]The 2023 IPCC AR6 report calculates that emissions need to decrease by 48% until 2030 from the 2019 emission levels to limit warming to 1.5°C with more than 50% likelihood with no or limited overshoot. Considering that global emissions in 2023 are above 2019 levels, this translates at least into 48%/6 = 8% annual rate (IPCC, 2023).

though this effect is often not significant. These results jointly suggest that while some of the emission reduction may be attributed to the sale of brown operations, green capital expenditures contribute to emission reductions. Responsible institutional investors seem to pressure firms to green their operations and do not allow firms to only sell off brown operation.

2.4 Conclusions

In this paper, I empirically show that responsible institutional investors practice stewardship and help accelerate green capital expenditure and thus the net zero transition. Firms with a greater share of responsible institutional investors, as measured by being a CA100+ signatory, are positively associated with future green capital expenditure, proxied with green debt in my main specification. Estimations that exploit plausibly exogenous variation based on firm's cross-listings confirm this finding. Institutional investors seem to engage with firms, particularly the largest emitters, and implement environmental governance mechanisms to incentivise managers to invest in green activities. Further, responsible institutional investor pressure seems to be complementary to other net zero transition pressures, which highlights the value of multi-faceted net-zero transition pressure. Overall, my results underscore the importance institutional investors can play in accelerating green capital expenditure, which are crucial to transition away from brown technologies and towards a global net-zero world. Responsible investor pressure and green capital expenditure appear to translate into emission reductions, the ultimate end goal. The effect seems to be at least of the size of a carbon tax. While the magnitude is still instufficient on its own, institutional investors as one factor of many can meaningfully contribute to align public firms on a net zero trajectory. To the extent that more institutional investors adopt sustainable preferences, the investment gap to be on a net-zero trajectory may be closed more quickly.

2.5 Tables

Table 2.1. Responsible investor share & green investment across time

The table reports annual sample averages across time for the available periods between 2006 and 2021 (2022). In Panel A, I report average responsible investment shares across time based on the CA100 SHARE in columns 1 to 4 worldwide and by headquarter region, the PRI SHARE in column 5 and the IMPACT-PRI SHARE in column 6. In Panel B, I report average green capital expenditure proxies based on the green debt instruments in column 1 to 4, the taxonomy based clean investment ratio in column 5, log absolute scope 1 emissions in column 6 and green innovation in column 7. All variables are defined in Table 2.11.

Panel A: Responsible investor proportion

	(1)	(2)	(3)	(4)	(5)	(6)
	CA100 SHARE				PRI SHARE	IMPACT-PRI SHARE
	worldwide	North America	Europe	Asia	worldwide	worldwide
2006					4.3	3.8
2007					10.4	9.3
2008					13.3	11.4
2009					17.2	12.8
2010					19.4	14.9
2011					21.7	16.7
2012					28.9	22.2
2013					36.4	29.0
2014					38.1	30.4
2015					41.2	29.5
2016					43.4	31.7
2017	1.5	1.1	3.0	1.0	49.1	39.8
2018	7.9	5.7	16.2	5.8	54.7	41.9
2019	10.0	6.2	18.5	8.9	58.3	48.8
2020	20.6	15.9	27.2	20.4	61.0	48.5
2021	24.8	18.8	30.6	25.4	65.2	48.9
Total	15.4	11.2	21.5	15.2	38.3	30.1

Panel B: Green capital expenditure measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GREENDEBT-DUMMY		GREENDEBT-AMOUNT	VERIFIED GREENDEBT	CLEANINVEST-	LOGS1TOT	GREENRATIOEP
	equally weighted	asset weighted	sum (mil. USD)	asset weighted	MENTRATIO		
2006	.	.	.	.	.	6.5	9.6
2007	.	.	.	.	.	6.5	9.8
2008	.	.	.	.	.	6.5	10.4
2009	.	.	.	.	.	6.4	11.9
2010	.	.	.	.	.	6.4	13.0
2011	.	.	.	.	.	6.4	13.9
2012	.	.	.	.	.	6.3	13.3
2013	0.1	1.8	2.5	1.6	.	6.2	12.9
2014	0.2	1.5	8.1	1.2	.	6.1	11.5
2015	0.2	4.9	10.2	4.8	.	6.0	12.5
2016	0.2	8.4	38.5	8.2	.	5.0	13.3
2017	0.4	11.7	37.4	10.4	.	4.9	13.2
2018	0.6	15.8	52.0	13.4	.	4.9	14.1
2019	1.0	20.5	85.8	18.2	10.7	4.9	14.7
2020	1.2	21.0	116.6	16.5	13.2	4.7	14.6
2021	2.6	29.0	273.1	21.8	14.5	4.7	14.3
2022	2.6	30.7	233.1	23.8	35.9	3.9	.
Total	0.9	14.7	86.8	12.2	13.4	5.4	12.7

Table 2.2. Summary statistics

The table reports sample first quartiles, median, third quartiles, averages, standard deviations and firm-year observations for institutional ownership variables in Panel A, green debt instruments in Panel B, other green capital expenditure measures in Panel C and control variables in Panel D. The sample period depends on the availability of data and goes at most from 2006 to 2022. All variables are defined in Table 2.11.

	(1) 1st Quartile	(2) Median	(3) 3rd Quartile	(4) Mean	(5) Std Dev	(6) Firm-year obs.
Panel A: Institutional ownership						
ALL INSTOSHIP	0.014	0.069	0.218	0.188	0.273	332085
CA100 SHARE	0.000	0.032	0.198	0.131	0.197	104532
PRI SHARE	0.012	0.270	0.649	0.358	0.343	329980
IMPACT-PRI SHARE	0.001	0.158	0.485	0.280	0.312	329980
Panel B: Green debt instruments						
GREENDEBT-DUMMY	0.000	0.000	0.000	0.009	0.096	212256
GREENDEBT-AMOUNT (intensive)	104.298	366.364	960.343	802.168	1437.107	1964
GREENDEBT-AMOUNT	0.000	0.000	0.000	7.422	158.112	212256
ASINH GREENDEBT-AMOUNT	0.000	0.000	0.000	0.059	0.631	212256
VERIFIED GREENDEBT-DUMMY	0.000	0.000	0.000	0.006	0.075	212256
ASINH VERIFIED GREENDEBT-AMOUNT	0.000	0.000	0.000	0.034	0.474	212256
SUSLINKDEBT-DUMMY	0.000	0.000	0.000	0.003	0.055	212256
ASINH SUSLINKDEBT-AMOUNT	0.000	0.000	0.000	0.017	0.348	212256
Panel C: Other green measures						
CLEANREVENUERATIO	0.000	0.000	0.050	0.125	0.273	7061
CLEANINVESTMENTRATIO	0.000	0.000	0.033	0.134	0.298	5923
LOGS1TOT	3.353	5.157	7.115	5.326	3.019	108362
LOGS2TOT	3.758	5.301	6.845	5.261	2.365	108438
LOGS3UPTOT	5.614	7.126	8.624	7.077	2.273	108487
S1INT	0.058	0.173	0.529	2.035	5.863	108487
S2INT	0.084	0.190	0.434	0.402	0.579	108487
S3UPINT	0.494	1.119	2.402	1.738	1.702	108487
GREENRATIOEP	0.000	0.000	0.114	0.129	0.264	47141
GREENRATIOWW	0.000	0.000	0.046	0.071	0.180	119662
GREENCITCOUNTEP	0.000	0.000	8.000	111.099	1542.497	47141
GREENCITCOUNTWW	0.000	0.000	3.000	114.310	1506.325	119662
GREENCITMAXEP	0.000	0.000	6.000	48.546	1336.650	47141
GREENCITMAXWW	0.000	0.000	2.000	30.581	860.856	119662
Panel D: Control variables						
LOGSIZE	4.361	5.688	7.096	5.756	2.064	332085
LEVERAGE	3.002	16.309	32.437	20.270	18.902	332085
ROE	−0.833	7.320	14.839	0.150	33.492	332085
INVEST/A	0.848	2.867	6.438	4.833	5.753	332085
M/B	0.822	1.484	2.848	2.425	2.742	332085
BETA	0.705	0.898	1.124	0.905	0.458	332085
VOLAT	0.070	0.104	0.155	0.129	0.104	332085
MOM	−0.022	0.002	0.024	−0.000	0.048	332085
RET	−0.050	0.003	0.065	0.014	0.142	332085
MSCI	0.000	0.000	0.000	0.140	0.347	332085

Table 2.3. CA100+ share & green debt

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT - DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. $CA100\,SHARE$ is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include industry-year and firm fixed effects. I cluster standard errors at the firm level. For the industry-year and firm fixed effect specifications, I additionally report the partial R2 and Oster (2019)'s delta based on 1.3 x partial R2. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
1YR-LAG CA100 SHARE	0.018***		0.018***		0.106***		0.105***	
	(0.002)		(0.003)		(0.015)		(0.017)	
3YR-LAG CA100 SHARE		0.031***		0.041***		0.206***		0.261***
		(0.006)		(0.007)		(0.036)		(0.045)
L1/L3 LOGSIZE (/100)	0.727***	1.075***	0.112	−0.008	4.885***	7.257***	0.767	0.097
	(0.058)	(0.090)	(0.087)	(0.170)	(0.388)	(0.593)	(0.544)	(1.117)
L1/L3 LOGPPE (/100)	0.199***	0.239***	0.153	0.433*	1.471***	1.820***	0.878	2.042
	(0.049)	(0.075)	(0.130)	(0.255)	(0.320)	(0.485)	(0.765)	(1.579)
L1/L3 LEVERAGE (/100)	0.018***	0.023***	−0.002	0.001	0.084***	0.111***	−0.016	0.026
	(0.003)	(0.005)	(0.005)	(0.010)	(0.020)	(0.032)	(0.029)	(0.061)
L1/L3 ROE (/100)	−0.007***	−0.014***	0.002	−0.002	−0.047***	−0.099***	0.016*	−0.017
	(0.001)	(0.002)	(0.001)	(0.003)	(0.007)	(0.015)	(0.009)	(0.021)
L1/L3 M/B (/100)	−0.154***	−0.229***	0.039*	0.023	−0.960***	−1.486***	0.334**	0.129
	(0.019)	(0.029)	(0.021)	(0.042)	(0.124)	(0.193)	(0.142)	(0.292)
L1/L3 INVEST/A (/100)	0.002	−0.006	0.015	−0.001	−0.023	−0.051	0.069	0.040
	(0.009)	(0.014)	(0.010)	(0.020)	(0.054)	(0.089)	(0.058)	(0.124)
L1/L3 BETA (/100)	0.015	−0.131	0.005	0.115	0.038	−0.742	−0.243	0.438
	(0.078)	(0.135)	(0.068)	(0.135)	(0.542)	(0.946)	(0.476)	(0.821)
L1/L3 VOLAT (/100)	1.722***	2.811***	−0.086	0.212	12.761***	21.264***	0.050	1.829
	(0.326)	(0.620)	(0.337)	(0.833)	(2.125)	(4.108)	(2.130)	(5.332)
L1/L3 MOM (/100)	−3.044***	−3.041*	−1.057	−0.927	−25.568***	−19.523*	−11.318**	−1.226
	(0.848)	(1.637)	(0.907)	(1.791)	(5.457)	(10.583)	(5.727)	(11.245)
L1/L3 RET (/100)	−0.013	0.612	−0.211	0.286	0.091	4.147*	−0.572	1.863
	(0.221)	(0.379)	(0.237)	(0.450)	(1.415)	(2.490)	(1.538)	(2.839)
L1/L3 MSCI	0.021***	0.030***	0.003	0.016*	0.140***	0.194***	0.023	0.074
	(0.002)	(0.004)	(0.006)	(0.009)	(0.015)	(0.023)	(0.036)	(0.061)
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0885	0.115	0.456	0.583
Partial-R2			.392	.514			.402	.528
Oster Delta			2.646	2.769			2.575	2.649

Table 2.4. Alternative responsible ownership measures & green debt

The unit of observation is firm-year. The sample period is 2017-2022 in Panel A to D and 2013 to 2022 in Panel E. The dependent variable is $GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. The key independent variables are $CA100-EARLY\ JOINER\ SHARE$ in Panel A, $CA100\ W/O\ BLK\ and\ SSGA\ SHARE$ in Panel B, $CA100\ W/O\ SHORT-TERM\ SHARE$ in Panel C, $CA100\ W/O\ HIGH\ EMISSION\ SHARE$ in Panel D and $IMPACT-PRI\ SHARE$ in Panel E. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
Panel A: CA100+ early joiners only								
1YR-LAG CA100-EARLY JOINERS SHARE	0.018***		0.014***		0.119***		0.089***	
	(0.003)		(0.004)		(0.021)		(0.025)	
3YR-LAG CA100-EARLY JOINERS SHARE		0.032***		0.044***		0.211***		0.289***
		(0.006)		(0.008)		(0.038)		(0.049)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0858	0.111	0.445	0.568	0.0884	0.115	0.455	0.583
Panel B: CA100+ without BlackRock and State Street Global Advisors								
1YR-LAG CA100 W/0 BLK and SSGA SHARE	0.011***		0.010***		0.067***		0.058***	
	(0.002)		(0.003)		(0.015)		(0.017)	
3YR-LAG CA100 W/0 BLK and SSGA SHARE		0.031***		0.041***		0.206***		0.261***
		(0.006)		(0.007)		(0.036)		(0.045)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0856	0.111	0.445	0.568	0.0883	0.115	0.455	0.583
Panel C: CA100+ without short-term investors								
1YR-LAG CA100 W/O SHORT-TERM SHARE	0.020***		0.020***		0.124***		0.117***	
	(0.003)		(0.003)		(0.018)		(0.019)	
3YR-LAG CA100 W/O SHORT-TERM SHARE		0.029***		0.044***		0.205***		0.286***
		(0.007)		(0.008)		(0.042)		(0.049)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0860	0.111	0.445	0.568	0.0886	0.115	0.456	0.583
Panel D: CA100+ without high emission investors								
1YR-LAG CA100 W/O HIGH-EMISSION SHARE	0.018***		0.022***		0.115***		0.131***	
	(0.003)		(0.003)		(0.017)		(0.019)	
3YR-LAG CA100 W/O HIGH-EMISSION SHARE		0.028***		0.042***		0.199***		0.279***
		(0.006)		(0.008)		(0.042)		(0.048)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0885	0.115	0.456	0.583
Panel E: Impact PRI signatories								
1YR-LAG IMPACT-PRI SHARE	0.004***		0.004***		0.032***		0.025***	
	(0.001)		(0.001)		(0.005)		(0.006)	
3YR-LAG IMPACT-PRI SHARE		0.003***		0.002*		0.024***		0.008
		(0.001)		(0.001)		(0.006)		(0.006)
Observations	207105	185526	206928	185286	207105	185526	206928	185286
R2	0.0568	0.0588	0.305	0.308	0.0574	0.0595	0.309	0.313
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table 2.5. CA100+ share & alternative green investment proxies

The unit of observation is firm-year. In Panel A, the sample period is 2018-2021 and the dependent variable is a clean taxonomy based revenue and investment measure, specifically *CLEANREVENUERATIO* in columns 1 to 4 and *CLEANINVESTMENTRATIO* in columns 5 to 8. In Panel B, the sample period is 2017-2021 and the dependent variable is a green innovation based measure, specifically *GREENRATIOEP* in columns 1 to 4 and *GREENCITCOUNTEP* in columns 5 to 8. In Panel C and D, the sample period is 2017-2022 and the dependent variables are emission based. In Panel C, the dependent variable is *LOGS1TOT* in columns 1 to 4 and *S1INT* in columns 5 to 8 and in Panel D the dependent variable is *LOGS2TOT* in columns 1 to 4 and *S2INT* in columns 5 to 8. *CA100SHARE* is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model except for Panel B, which is estimated using Poisson pseudo-maximum likelihood. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Clean taxonomy measures	CLEANREVENUERATIO				CLEANINVESTMENTRATIO			
1YR-LAG CA100 SHARE	0.121**		0.020		0.257***		0.040	
	(0.059)		(0.025)		(0.061)		(0.034)	
3YR-LAG CA100 SHARE		0.088		0.021		0.261***		0.030
		(0.087)		(0.033)		(0.089)		(0.058)
Observations	6006	3988	5971	3952	6103	4056	6103	4056
R2	0.522	0.521	0.969	0.975	0.484	0.485	0.916	0.924
Panel B: Green innovation	GREENRATIOEP				GREENCITCOUNTEP			
1YR-LAG CA100 SHARE	0.158		0.105		4.281**		5.385**	
	(0.175)		(0.227)		(2.080)		(2.345)	
3YR-LAG CA100 SHARE		0.258		1.033**		5.016***		9.128*
		(0.352)		(0.523)		(1.630)		(5.144)
Observations	11581	4864	5589	1820	11370	4510	4664	1190
Pseudo R2	0.115	0.124	0.231	0.225	0.748	0.579	0.946	0.932
Panel C: Scope 1 emissions	LOGS1TOT				S1INT			
1YR-LAG CA100 SHARE	−0.222***		−0.122***		−0.522***		−0.065	
	(0.082)		(0.044)		(0.187)		(0.103)	
3YR-LAG CA100 SHARE		−0.328*		−0.165*		−0.412		−0.274**
		(0.172)		(0.090)		(0.341)		(0.125)
Observations	50693	24905	49666	23583	50754	24940	49726	23627
R2	0.767	0.753	0.971	0.985	0.578	0.579	0.956	0.978
Panel D: Scope 2 emissions	LOGS2TOT				S2INT			
1YR-LAG CA100 SHARE	0.116*		−0.063*		0.097***		−0.010	
	(0.067)		(0.037)		(0.024)		(0.014)	
3YR-LAG CA100 SHARE		0.233*		−0.249***		0.177***		−0.052*
		(0.140)		(0.086)		(0.043)		(0.029)
Observations	50740	24927	49712	23609	50754	24940	49726	23627
R2	0.739	0.718	0.961	0.979	0.467	0.457	0.909	0.959
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table 2.6. Asian/European firms' cross-listing balance table

The unit of observation is firm-year. The table presents the balance test post-matching for the four years prior to cross-listing in the United States. Panel A reports the balance test across the treatment and control sample for the variables on which I matched. Panel B reports the balance test across key outcome variables in levels and one-year changes. I report the mean, stand deviation, median and count for each sample as well as the difference and p-value between the two samples.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Treat sample				Control sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: Match variables										
LOGSIZE	6.524	2.149	6.201	337	6.754	2.349	6.827	1042	−0.230	0.103
ROE	−16.469	49.817	2.203	337	−8.884	45.727	7.641	1042	−7.585	0.015
LEVERAGE	19.337	19.159	15.974	337	18.640	16.935	15.005	1042	0.696	0.559
INVEST/A	4.115	5.424	2.003	337	4.076	4.196	2.965	1042	0.038	0.906
Panel B: Non-match variables										
US SHARE	0.354	0.352	0.245	337	0.216	0.236	0.154	1042	0.138	0.000
CA100 SHARE	0.098	0.149	0.042	85	0.114	0.157	0.048	264	−0.016	0.402
IMPACT-PRI SHARE	0.251	0.240	0.179	329	0.310	0.268	0.282	1018	−0.059	0.000
1YR-CHG US SHARE	0.344	1.219	−0.000	257	0.215	0.916	0.021	743	0.129	0.156
1YR-CHG CA100 SHARE	2.440	4.009	1.700	43	3.952	8.309	1.134	115	−1.511	0.106
1YR-CHG IMPACT-PRI SHARE	0.437	1.238	0.147	268	0.510	1.606	0.099	822	−0.073	0.493
GREENDEBT-DUMMY	0.006	0.074	0.000	181	0.005	0.072	0.000	569	0.000	0.970
LOGS1TOT	4.329	3.524	4.967	159	5.916	2.729	5.961	514	−1.587	0.000
S1INT	0.617	1.510	0.149	159	1.254	3.295	0.153	514	−0.637	0.004
1YR-CHG SCOPE1TOT	0.158	0.619	0.043	147	0.097	0.422	0.022	478	0.061	0.282
1YR-CHG SCOPE1INT	0.001	0.290	−0.013	147	0.016	0.310	−0.018	478	−0.015	0.618

Table 2.7. CA100+ share & environmental governance

The unit of observation is firm-year. In Panel A, the sample period is 2017-2022 and the dependent variable is *SBTSIGN* in columns 1 and 2 and *SBTTGT* in columns 3 and 4. In Panel B, the sample period is 2017-2021. The dependent variable is *CSO* in columns 1 and 2, *EXECSUSRESP* in columns 3 and 4, and *EXECSUSCOMP* in columns 5 and 6. *CA*100 *SHARE* is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Decarbonization targets

	(1)	(2)	(3)	(4)
	SBTSIGN		SBTTGT	
1YR-LAG CA100 SHARE	0.042***		0.027***	
	(0.003)		(0.002)	
3YR-LAG CA100 SHARE		0.068***		0.043***
		(0.009)		(0.006)
Controls	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes
Observations	104482	55214	104482	55214
R2	0.714	0.817	0.709	0.843

Panel B: Executive environmental responsibilities and incentives

	(1)	(2)	(3)	(4)	(5)	(6)
	CSO		EXECSUSRESP		EXECSUSCOMP	
1YR-LAG CA100 SHARE	0.018		0.098***		0.101***	
	(0.017)		(0.025)		(0.031)	
3YR-LAG CA100 SHARE		0.055**		0.095**		0.050
		(0.024)		(0.040)		(0.050)
Controls	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes
Observations	26173	10441	26173	10441	26173	10441
R2	0.804	0.890	0.662	0.829	0.717	0.836

Table 2.8. Responsible investor impact on investor target firms

The unit of observation is firm-year. The sample period is 2017-2022, except for 2017 to 2021 in Panel C. In Panel A, the dependent variable is $GREENDEBT - DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. In Panel B, the dependent variable is $SBTSIGN$ in columns 1 to 4 and $SBTTGT$ in columns 5 to 8. In Panel C, the dependent variable is CSO in columns 1 to 4, $EXECSUSRESP$ in columns 5 to 8, and $EXECSUSCOMP$ in columns 9 to 13. The key independent variables are $CA100\,SHARE$ and its interaction with $HIGHESTEMITTERS$, a dummy equal to one for the for firms in the top 200 highest emitters in 2016 by total scope 1 emissions, as well as its interaction with $CA100TARGET$, a dummy equal to one if the firm is part of the target company set of the CA100+ initiative. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Green debt instruments								
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
1YR-LAG CA100 SHARE	0.016***	0.016***			0.092***	0.094***		
	(0.003)	(0.003)			(0.016)	(0.017)		
1YR-LAG CA100 SHARE X HIGHEST EMITTERS	0.285***				2.108***			
	(0.092)				(0.615)			
1YR-LAG CA100 SHARE X CA100 Target		0.357***				2.948***		
		(0.094)				(0.725)		
3YR-LAG CA100 SHARE			0.038***	0.039***			0.246***	0.250***
			(0.007)	(0.007)			(0.044)	(0.044)
3YR-LAG CA100 SHARE X HIGHEST EMITTERS			0.472***				3.193***	
			(0.183)				(1.224)	
3YR-LAG CA100 SHARE X CA100 Target				0.322				2.822*
				(0.235)				(1.712)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104460	104460	55206	55206	104460	104460	55206	55206
R2	0.446	0.446	0.569	0.569	0.456	0.457	0.583	0.583
Panel B: Decarbonization targets as environmental governance								
	SBTSIGN				SBTTGT			
1YR-LAG CA100 SHARE	0.041***	0.041***			0.026***	0.025***		
	(0.003)	(0.003)			(0.002)	(0.002)		
1YR-LAG CA100 SHARE X HIGHEST EMITTERS	0.151**				0.128**			
	(0.065)				(0.056)			
1YR-LAG CA100 SHARE X CA100 TARGET		0.326***				0.526***		
		(0.105)				(0.104)		
3YR-LAG CA100 SHARE			0.067***	0.067***			0.042***	0.041***
			(0.009)	(0.009)			(0.006)	(0.006)
3YR-LAG CA100 SHARE X HIGHEST EMITTERS			0.111				0.065	
			(0.110)				(0.078)	
3YR-LAG CA100 SHARE X CA100 TARGET				0.057				0.383**
				(0.208)				(0.174)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104482	104482	55214	55214	104482	104482	55214	55214
R2	0.714	0.714	0.817	0.817	0.709	0.711	0.843	0.844

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel C: Executive environmental responsibilities as environmental governance												
	CSO				EXECSUSRESP				EXECSUSCOMP			
1YR-LAG CA100 SHARE	0.015	0.015			0.091***	0.095***			0.098***	0.102***		
	(0.017)	(0.017)			(0.025)	(0.025)			(0.031)	(0.031)		
1YR-LAG CA100 SHARE X HIGHEST EMITTERS	0.107				0.331**				0.151			
	(0.086)				(0.145)				(0.135)			
1YR-LAG CA100 SHARE X CA100 TARGET		0.318				0.285				−0.105		
		(0.197)				(0.201)				(0.186)		
3YR-LAG CA100 SHARE			0.048**	0.047**			0.091**	0.094**			0.046	0.053
			(0.024)	(0.024)			(0.040)	(0.040)			(0.049)	(0.050)
3YR-LAG CA100 SHARE X HIGHEST EMITTERS			0.395				0.754				0.904**	
			(0.297)				(0.472)				(0.425)	
3YR-LAG CA100 SHARE X CA100 TARGET				0.382				−0.038				−0.368
				(0.279)				(0.393)				(0.480)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	26173	26173	10441	10441	26173	26173	10441	10441	26173	26173	10441	10441
R2	0.804	0.805	0.888	0.888	0.662	0.662	0.829	0.829	0.717	0.717	0.837	0.836

Table 2.9. Moderating factors of the CA100+ share & green investment relationship

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT - DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. The key independent variables are $CA100\ SHARE$ and its interaction with $LOGSIZE$ and ROE. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
1YR-LAG CA100 SHARE	-0.136^{***}		0.018^{***}		-0.910^{***}		0.107^{***}	
	(0.010)		(0.003)		(0.071)		(0.017)	
1YR-LAG CA100 SHARE X LOGSIZE	0.028^{***}				0.184^{***}			
	(0.002)				(0.014)			
1YR-LAG CA100 SHARE X			0.026^{***}				0.159^{***}	
(ROE/100)			(0.004)				(0.026)	
3YR-LAG CA100 SHARE		-0.185^{***}		0.041^{***}		-1.246^{***}		0.264^{***}
		(0.024)		(0.007)		(0.161)		(0.045)
3YR-LAG CA100 SHARE X LOGSIZE		0.043^{***}				0.287^{***}		
		(0.005)				(0.035)		
3YR-LAG CA100 SHARE X				0.026^{**}				0.163^{**}
(ROE/100)				(0.012)				(0.076)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.448	0.570	0.445	0.568	0.459	0.584	0.456	0.583

Table 2.10. Socio-political environment moderating CA100+ share & green debt

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT-DUMMY$. The key independent variables are $CA100SHARE$ and its interaction with $TIME$, a time trend variable, region indicators for Europe, Asia and others while omitting North America, $NET-ENVRIONMENTALTAX$, a country level measure of envrionmental tax collections less fossil fuel subsidies relative to GDP, $INTPOLICY$, a measure of international policy tightness, $DOMPOLICY$, a measure of domestic policy tightness, and $NGOCAMPAIGN-DUMMY$, a dummy equal to one if the number of campaigns a firm is exposed to increased relative to the last year. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one year in Panel A or three years in Panel B. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
			GREENDEBT-DUMMY			
Panel A: One-year lag						
1YR-LAG CA100 SHARE	0.048***	−0.002	0.021***	0.001	0.010*	0.015***
	(0.005)	(0.008)	(0.005)	(0.006)	(0.006)	(0.003)
1YR-LAG CA100 SHARE X TIME	0.016***					
	(0.002)					
1YR-LAG CA100 SHARE X EUROPE		0.050***				
		(0.011)				
1YR-LAG CA100 SHARE X ASIA		0.012				
		(0.009)				
1YR-LAG CA100 SHARE X OTHERS		0.004				
		(0.012)				
1YR-LAG CA100 SHARE X			0.210***			
NET-ENVIRONMENTAL TAX			(0.072)			
1YR-LAG CA100 SHARE X				0.030***		
INTPOLICY				(0.011)		
1YR-LAG CA100 SHARE X					0.012	
DOMPOLICY					(0.010)	
1YR-LAG CA100 SHARE X NGO						0.181***
CAMPAIGN-DUMMY						(0.039)
1YR-LAG NET-ENVIRONMENTAL TAX			−0.055			
			(0.042)			
1YR-LAG INTPOLICY				0.004		
				(0.003)		
1YR-LAG DOMPOLICY					0.007**	
					(0.003)	
1YR-LAG NGO-CAMPAIGN-DUMMY						−0.036***
						(0.008)
Observations	104460	104460	76958	89028	89028	104460
R2	0.445	0.445	0.465	0.453	0.453	0.446
Panel B: Three-year lag						
3YR-LAG CA100 SHARE	0.043***	0.005	0.047***	−0.007	0.023	0.038***
	(0.014)	(0.014)	(0.010)	(0.017)	(0.016)	(0.007)
3YR-LAG CA100 SHARE X TIME	0.002					
	(0.009)					
3YR-LAG CA100 SHARE X EUROPE		0.064***				
		(0.020)				
3YR-LAG CA100 SHARE X ASIA		0.018				
		(0.017)				
3YR-LAG CA100 SHARE X OTHERS		0.018				
		(0.025)				
3YR-LAG CA100 SHARE X			0.324*			
NET-ENVIRONMENTAL TAX			(0.182)			
3YR-LAG CA100 SHARE X				0.070***		
INTPOLICY				(0.026)		
3YR-LAG CA100 SHARE X					0.031	
DOMPOLICY					(0.030)	
3YR-LAG CA100 SHARE X NGO						0.182*
CAMPAIGN-DUMMY						(0.101)
3YR-LAG NET-ENVIRONMENTAL TAX			−0.120*			
			(0.070)			
3YR-LAG INTPOLICY				0.007*		
				(0.004)		
3YR-LAG DOMPOLICY					0.007*	
					(0.004)	
3YR-LAG NGO-CAMPAIGN-DUMMY						−0.027**
						(0.013)
Observations	55206	55206	43629	46873	46873	55206
R2	0.568	0.568	0.578	0.573	0.573	0.569
Controls	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes

Table 2.11. Variables Definition

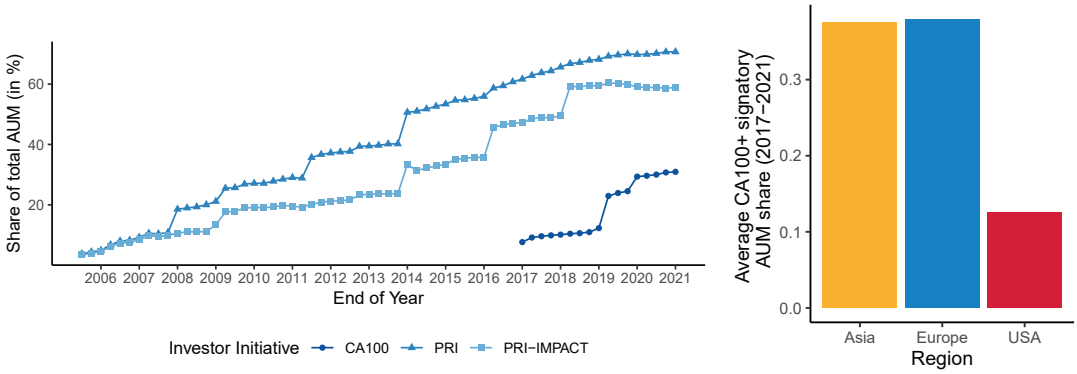
I describe the definitions of institutional ownership variables in Panel A, green investment variables in Panel B, environmental governance variables in Panel C, Control variables in Panel D and Interaction variables in Panel E.

Variable Name	Variable Definition	Data Source
Panel A: Institutional ownership variables		
CA100 SHARE	CA100+ instituional ownership divided by total institutional ownerhsip	CA100+ & FactSet
PRI SHARE	PRI instituional ownership divided by total institutional ownerhsip	PRI & FactSet
IMPACT-PRI SHARE	IMPACT-PRI investors are defined as signtories who report that at least 50% of their engagements are comprehensive or have more than 100 engagements and at least one comprehensive engagement. This is based on the PRI public survey question LEA11.1 and LEA11.2 (LEA9.1 and LEA 9.2 in 2019 and 2020). I fill survey answers forward and backward if a year is missing, assuming that signatories exhibit the same engagement style if they do not disclose or have not yet submitted a survey. IMPACT-PRI PROP is the ownership of IMPACT-PRI investors divided by total institutional ownerhsip	PRI & FactSet
US PROP	US instituional ownership divided by total institutional ownership	FactSet
Panel B: Green investment variables		
GREENDEBT-DUMMY	equals one if a firm issues at least one self-classified or externally verified sustainability bond or loan, green bond or loan or sustainability-linked bond or loan	Bloomberg
ASINH(GREENDEBT)	inverse hyperbolic (IHS) transformation of the dollar amount of proceeds raised through self-classified or externally verified sustainability bond or loan, green bond or loan or sustainability-linked bond or loan	Bloomberg
VERIFIED GREENDEBT-DUMMY	equals one if a firm issues at least one externally verified green bond or loan	Bloomberg
ASINH(GREENBOND)	inverse hyperbolic (IHS) transformation of the dollar amount of proceeds raised through externally verified green bond or loan	Bloomberg
SUSLINKBOND-DUMMY	equals one if a firm issues at least one externally verified sustainability-linked bond or loan	Bloomberg
ASINH(SUSLINKBOND)	inverse hyperbolic (IHS) transformation of the dollar amount of proceeds raised through externally verified sustainability-linked bond or loan	Bloomberg
CLEANREVENUERATIO	clean revenue divided by total revenue	Corporate Knights
CLEANINVESTMENTRATIO	clean investments (including capital expenditures, R&D, and acquisitions) divided by total investments	Corporate Knights
GREENRATIOWW	number of green patent family applications divided by the total number of all patent family applications at any patent office worldwide	Orbis IP
GREENRATIOEP	number of green patent applications divided by the total number of all patent applications at the European Patent Office	Orbis IP
GREENCITMAXWW	maximum patent citations of all green patent family applications at any patent office worldwide	Orbis IP
GREENCITMAXEP	maximum patent citations of all green patent applications at the European Patent Office	Orbis IP
GREENCITCOUNTWW	citation weighted sum of green patent family applications at any patent office worldwide	Orbis IP
GREENCITCOUNTEP	citation weighted sum of green patent applications at the European Patent Office	Orbis IP
Panel C: Environmental governance variables		
SBTSIGN	equals one if a firm is a SBTi signatory, i.e. it has commited to set a target or has an approved target	Science-Based Target initiative
SBTTGT	equals one if a firm has a SBTi approved target	Science-Based Target initiative
CSO	equals one if a firm has at least one chief sustainability officer	Refinitiv
EXECSUSRESP	equals one if a firm has at least one executive with sustainability responsibilities	Refinitiv
EXECSUSCOMP	equals one if a firm has at least one executive with sustainability targets for its compensation	Refinitiv
Panel D: Control variables		
LOGSIZE	natural logarithm of market capitalization (in $ million)	FactSet
LOGPPE	natural logarithm of plant, property & equipment (in $ million)	FactSet
LEVERAGE	book value of leverage defined as the book value of debt divided by the book value of assets	FactSet
ROE	return on equity	FactSet
M/B	market value of equity divided by the book value of equity	FactSet
BETA	firm-level market beta estimated over the one-year period	FactSet
VOLAT	monthly stock return volatility calculated over the one-year period	FactSet
MOM	cumulative stock return over the one-year period	FactSet
RET	last December stock return	FactSet
INVEST/A	capital expenditure divided by book value of assets	FactSet
MSCI	an indicator variable equal to one if a stock is part of MSCI ACWI, and zero otherwise	FactSet
Panel E: Interaction variables		
HIGHEST EMITTERS	equals one if firms are part of the top 100 largest emitters in total scope 1, 2 and upstream 3 in 2006	S&P Global Trucost
CA100 TARGET	equals one if firm is part of the focus group for engagement of the CA100+ iniative	CA100+
ENERGY SECTOR	equals one if firm is in US SIC industry x, y, z	FactSet
TIME	time trend variable	n/a
EUROPE	equals one if a firm's headquarter is located in Europe	FactSet
ASIA	equals one if a firm's headquarter is located in Asia	FactSet
NET ENVIRONMENTAL TAXES	Country level environmental taxes relative to GDP minus fossil fuel subsidies relative to GDP	IMF
INTPOLICY	international policy tightness measure	Germanwatch
DOMPOLICY	domestic policy tightness measure	Germanwatch
NGO-CAMPAIGN DUMMY	equals one if the number of campaigns a firm is exposed to increased relative to the last year and zero if the number of campaings decreased, remained flat or the firm is not covered	Sigwatch-PSE

2.6 Figures

Figure 2.1. Sustainable investing across time and region

In Panel A, the sample period is 2006 to 2021. I report the proportion of assets under management by CA100+ signatories in dark blue as well as PRI and IMPACT-PRI signatories in lighter blues relative to total institutional assets under management. In Panel B, the sample period is 2017 to 2021. I report total proportion of institutional assets under management that is owned by CA100+ signatories during this period in Asia, Europe and the United States.



(a) Institutional investor signatories AUM share over time

(b) CA100+ signatory share by region

Figure 2.2. European and Asian Firms Cross-Listing in the United States

I report the number of Asian and European headquartered firms that cross-listed in the United States per year between 2007 and 2021.

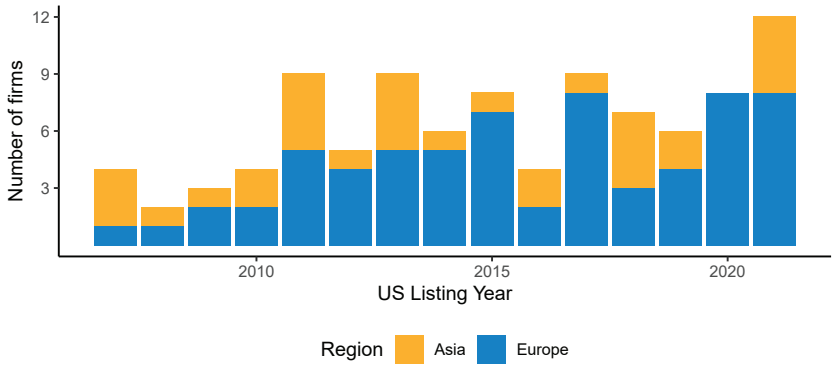
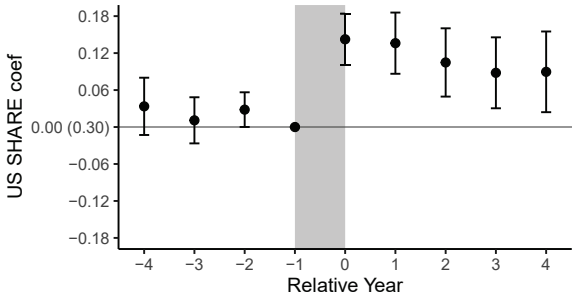
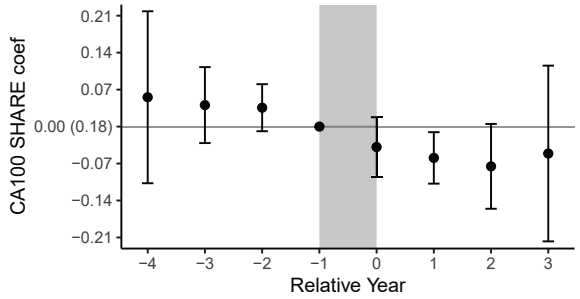


Figure 2.3. Cross-Listing in the United States and Institutional Ownership

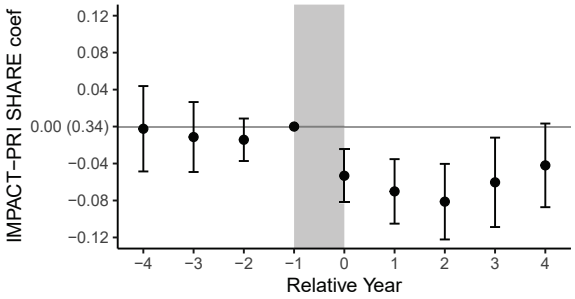
The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2007 to 2021, except for Panel B where it is between 2017 to 2021. The dependent variable is the American share, the share of American institutional ownership relative to total institutional ownership, in Panel A, CA100+ SHARE in Panel B and IMPACT-PRI SHARE in Panel C. Controls include one-year lagged LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) AMERICAN SHARE



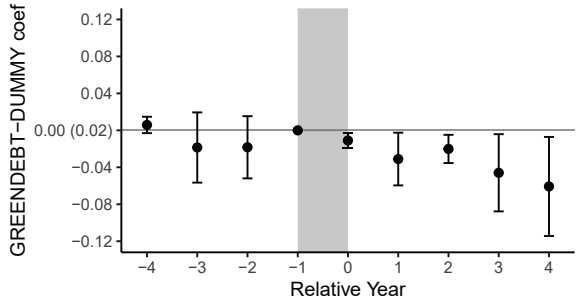
(b) CA100+ SHARE



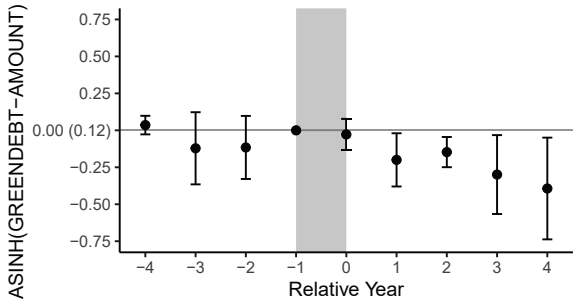
(c) IMPACT-PRI SHARE

Figure 2.4. Cross-Listing in the United States and Green CapEX

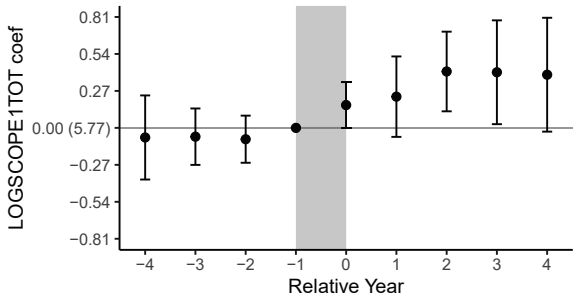
The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2014 to 2021 in Panel A and B, respectively 2007 to 2021 in Panel C. The dependent variable is GREENDEBT-DUMMY in Panel A, ASINH(GREENDEBT) in Panel B and LOGS1TOT in Panel C. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) GREENDEBT-DUMMY



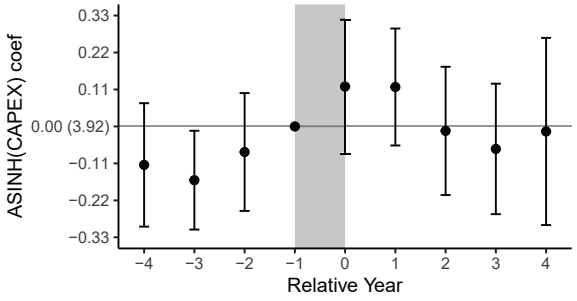
(b) ASINH(GREENDEBT)



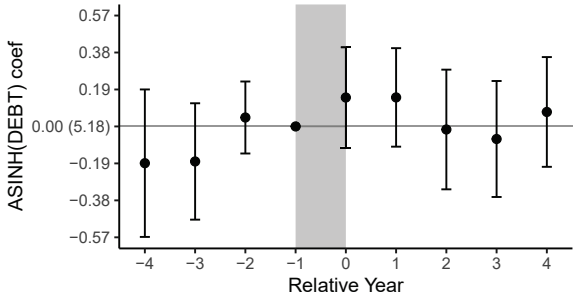
(c) LOGS1TOT

Figure 2.5. Cross-Listing in the United States and General Investment

The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2007 to 2021. The dependent variable is ASINH(CAPEX) in Panel A and ASINH(DEBT) in Panel B. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) ASINH(CAPEX)



(b) ASINH(DEBT)

Figure 2.6. Number of engagements by CA100+ and Non-CA100+ investors

The sample is 2013 to 2019. The histogram plots the number of engagements by CA100+ signatories respectively non-CA100+ signatories with a bindwidth of 50 engagements using the PRI survey data. All respondents are also PRI signatories.

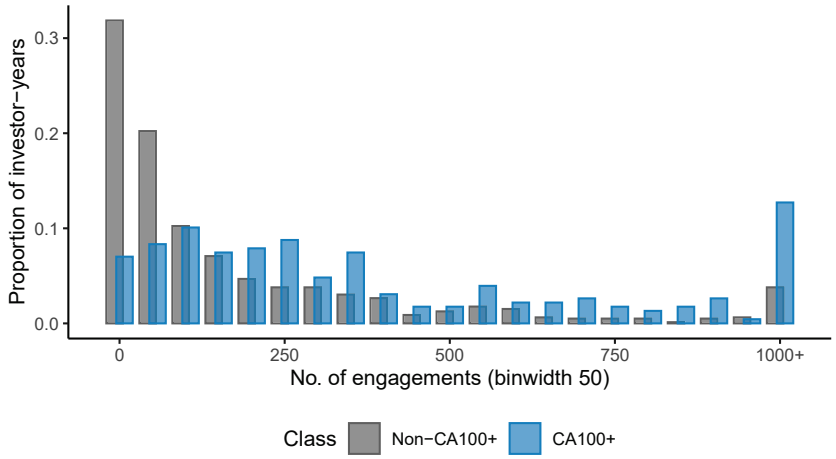
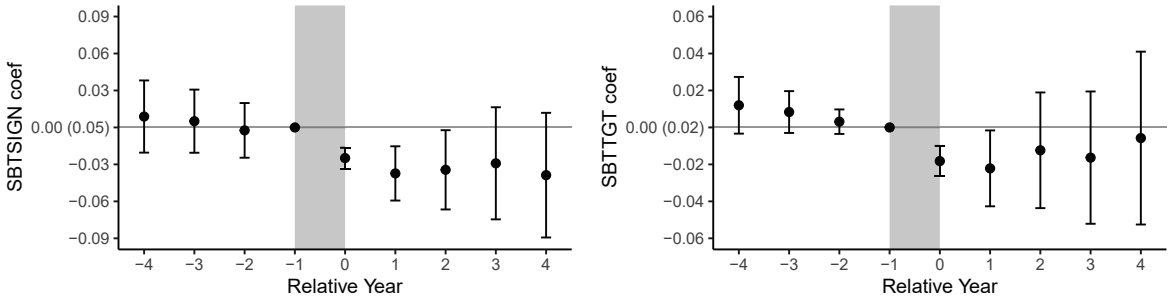


Figure 2.7. Cross-Listing in the United States and decarbonization targets

The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2015 and 2021. The dependent variable is SBTSIGN in Panel A and SBTTGT in Panel B. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) SBTSIGN **(b)** SBTTGT

Chapter 3

The CO2 Question: Technical Progress and the Climate Crisis

With Patrick Bolton and Marcin Kacperczyk[1]

We are in the early stages of a sustainability revolution. It will have the magnitude of the industrial revolution yet the speed of the digital revolution. Al Gore (2020)

There is no doubt that the energy sector will only reach net-zero emissions if there is a significant and concerted global push to accelerate innovation. Energy Policy Perspectives 2020 IEA

3.1 Introduction

How are innovation activities and technological advances shaped by the prospect of an approaching climate change crisis? In this paper, we explore corporate green innovation activity around the world and its effects on corporate behavior, in particular on future corporate carbon emissions. According to the IPCC (2021) report, to avoid

[1]This chapter is adapted from the co-authored working paper "The CO2 Question: Technical Progress and the Climate Crisis", for which I was jointly responsible for the design, data collection, data analysis, and writing up.

an increase in average temperatures greater than 1.5°C, global net carbon emissions must be reduced to zero by 2050. To have any hope of attaining this goal, governments around the world have stepped up their policies to curb carbon emissions and accelerate the transition to renewable energy sources.

Yet nearly all analysts agree that a successful global decarbonization cannot be founded only on regulations. It necessarily entails major technical advances in substitute energy sources and other technologies to reduce or capture carbon emissions. According to the IEA (2020), "Reducing global CO2 emissions will require a broad range of different technologies working across all sectors of the economy in various combinations and applications. These technologies are at widely varying stages of development."

Much R&D that is touted as green mainly takes the form of efficiency improvements in energy use. Primary examples are fuel efficiency gains in transport, electricity efficiency gains in refrigeration, air-conditioning, computing, lighting, and heating. The promise of these technological improvements is that the environmental impact of consumption in terms of carbon emissions will become smaller and smaller. However, as Jevons (1865) first noted about coal consumption, greater energy efficiency—by lowering the energy cost of consumption—could induce an increase in aggregate demand for energy, which could undo the anticipated reduction in energy use: "It is wholly a confusion of ideas to suppose that the economical use of fuel is equivalent to a diminished consumption." Indeed, despite all the technological improvements in fossil energy use, we have still not seen a global decoupling of economic growth and carbon emissions.

The title of our paper is a reference to the title of Jevons's (1865) book, *The Coal Question*, as the same economic problem he saw for the consumption of coal, which is only available in limited supply, arises for CO2 concentration in the atmosphere, which can only be accumulated to a limited amount if we are to avoid global overheating. The main question we are concerned with in this study is the impact of green innovation

on future corporate carbon emissions. What has come to be known as the *Jevons paradox* (and is also referred to as the *rebound effect*) is a warning that green technological progress is not necessarily synonymous with carbon emission reductions because technological improvements that reduce fossil fuel energy reliance also boost economic activity. It is unclear a priori what the net effect is on carbon emissions of respectively green R&D (that is not related to fossil fuels) and brown efficiency-improving R&D (that improves the energy efficiency of fossil fuel-based technologies), given that consumption and production are endogenous, and that any successful innovation generates additional economic activity. Even pure green innovations, that reduce direct or downstream emissions, may cause an increase in brown electricity production (scope 2 emissions) or emissions in the supply chain (especially upstream), an impact we define as the *displacement effect.*

A related question we are concerned with is the extent to which companies with high carbon emissions move away from fossil fuel-based technologies and embrace green innovation. More generally, how much do corporate characteristics (the line of business the company is in; the technologies it is using) determine the innovation activities a company engages in? What companies, in which sectors, have been the source of most green R&D?

We can address these questions by combining three global datasets on respectively corporate patent filings, corporate financial reports, and corporate (direct and indirect) carbon emissions covering the period from 2005 to 2020. All in all, our data covers more than 136 million patents held by 2.3 million firms. Based on a patent's Cooperative Patent Classification (CPC), we can sort patents into three broad categories, green patents (which concern technological improvements in environmental impacts of economic activities), brown efficiency-improving patents (which achieve advances in fossil energy efficiency), and other patents that are not directly related to the environment or to energy. For each firm we can determine the intensity of their green or brown innovation activities by calculating the ratio of the number of their green (respectively brown efficiency) patents to the total number of patents they have filed. We

calculate these ratios based on either worldwide patent filings or on filings with the European patent office, which are known to be more reliable. We can also weigh the importance of each patent based on the number of citations.

We begin our analysis by exploring how these measures of corporate green (or brown) innovation activity are associated with firm characteristics (our analysis covers corporate innovative activity around the world, which allows us to control for country, sector, and firm characteristics). A first contribution of our study is to provide a picture of green innovation activity across countries, sectors, firms, and over time. For example, we find that 22.3% of publicly listed companies engage in innovation, while only 1.6% of private companies file patents in a given year. Furthermore, we find that the distribution of countries contributing at least one green patent is highly skewed, with the top ten countries contributing most green patents. This is also true for the distribution across sectors and firms, with some sectors, such as multi-Utilities, Electric Utilities, Oil, Gas & Consumable Fuels, and Independent Power and Renewable Electricity production standing out for their high ratios of green to total number of patents. Across sectors just over 1% of all firms have filed at least one green patent. We also find that green innovation activity has steadily risen over our sample period, with the average patent ratio rising from 0.080 in 2005 to 0.130 in 2020.

A central idea in the economics of innovation literature is the *Arrow replacement effect* (Arrow, 1962), which refers to the lower incentive to innovate for an established firm with market power if the innovation replaces an existing technology that is working and is profitable. Another important idea for our analysis is learning-by-doing (Arrow, 1971), which means that companies master the technologies they use better, the more they have been using them. A key prediction for our analysis that derives from these two effects is that profitable companies with operations based on fossil fuel energy are less likely to engage in green innovation, a new technology they are less familiar with. If a company engages in green innovation, it is more likely to be a new entrant that is less dependent on fossil fuel-based technologies.

Consistent with these predictions, we find that companies with greater experience with brown technologies (as measured by the stock of brown efficiency patents they already own) are less likely to engage in green innovation and companies with greater experience with green technologies (as measured by the stock of green patents they already own) are less likely to engage in brown efficiency innovation.[2] Furthermore, we find that that brown companies (with higher emissions and that are older) do not tend to engage in green R&D. This is true in particular for companies with higher indirect (scope 3) emissions, which suggests that there is a broader replacement effect at work than the one identified by Arrow: brown companies appear to be locked into fossil-fuel dependent technologies through their production networks. If input suppliers or downstream firms/customers also rely on fossil fuel-dependent technologies, it is more difficult for an individual firm in the supply chain to switch to green technologies. A key implication from this latter finding is that, in order to induce firms to transition from brown to green technologies, industrial policy may be necessary to coordinate this transition across all firms linked through the supply chain.

Our findings that green R&D is more likely to be undertaken by new entrants and brown efficiency R&D is more likely for established companies with operations that are based on fossil fuel energy are consistent with earlier studies that find evidence that innovation is path dependent (Acemoglu, 2002; Popp, 2002; Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen, 2016). Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen (2016) consider a panel of automobile manufacturers and explore the extent to which these companies produce innovations on combustion-engine cars versus electric, hydrogen or hybrid engine vehicles. Their main finding is that specialization in innovation activity in clean (vs brown) technologies is self-reinforcing. Our study extends this evidence in support of the path-dependency view of innovation to all sectors, across countries, not just the automobile sector.

[2] A case in point is the energy company Halliburton. In response to a recent SEC question on its exposure to carbon transition risk it stated that "We believe that one of the significant risks that we face in energy transition is that we will be unable to innovate in a timely, cost-efficient manner, or at all." (See *Climate risks gain corporate acknowledgment after SEC prodding* by Patrick Temple-West, Financial Times 30 December 2022). We show in Figure IA.II that most of Halliburton's innovation activity in recent years has been in brown innovation, which has steadily increased over time.

Even if innovation is path dependent, and even if brown firms are less likely to undertake green R&D, we find that there has been a steady rise in the number of green patent filings (as shown in Figure 3.1). It is therefore possible that the promise of a sustainability revolution could be fulfilled. We explore this question next by looking at the effects of green R&D on future corporate carbon emissions and other policy outcomes. How has green R&D affected corporate carbon emissions, capital expenditures, and other policies? According to the IEA (2020) "Around half of the cumulative emissions reductions that would move the world onto a sustainable trajectory come from four main technology approaches. These are the electrification of end-use sectors such as heating and transport; the application of carbon capture, utilization and storage; the use of low-carbon hydrogen and hydrogen-derived fuels; and the use of bioenergy. However, each of these areas faces challenges in making all parts of its value chain commercially viable in the sectors where reducing emissions is hardest". Another issue is the extent to which the benefits of technological improvements in terms of carbon efficiency are undone by rebound effects (Jevons, 1865). Finally, some of the green innovations may lead to a displacement in emissions.

Our main finding on the effects of green innovation on corporate outcomes is that there has been no significant impact on future carbon emissions reductions. Whether in the short run (one year), or medium run (three & five years ahead), we do not find any significant effect of green innovation on direct and indirect corporate carbon emissions of the innovating firms. Consistent with the Jevons paradox, we find that brown efficiency innovation does result in lower future carbon intensity, but this benefit is undone by higher sales, which overall result in higher future emissions.

We also analyse how aggregate sectoral changes in emissions are associated with green R&D on the presupposition that innovation could be of use not just for the innovator but also for other firms operating in the same sector. However, we do not find any significant spillover effects of green innovation on the carbon emissions of either innovating or non-innovating firms in the same (GICS-6) sector. Yet, consistent with the displacement effect and the greater reliance on brown electricity, we do find that

green innovation is associated with subsequent increases in scope 2 emissions of the same sector. In contrast, brown efficiency innovation does not predict future emission changes of other innovating firms in the same sector. However, it does benefit non-innovating firms whose direct and indirect emissions go down. But this decrease is mostly a consequence of lower sales for this group of firms.

We also find that the association of innovation activity by publicly listed companies and their future emissions is not strongly correlated with the same association of innovation and future emissions by privately held firms. That is, innovation by publicly listed companies has a stronger positive effect on their future scope 2 emissions than the innovation by privately held firms on their future scope 2 emissions. Furthermore, we do not find any spillover effects broadly speaking across sectors or across countries. The one notable exception is our finding that an increase in green innovation predicts subsequent reductions in scope 3 downstream emissions of broadly related industries.

Another indirect channel through which innovation can affect future emissions of non-innovating firms is through changes in the market shares of innovating firms. We find that firms with higher green patent ratios tend to lose market share to other firms that have higher emissions, a form of displacement effect. Finally, our third main finding on the effects of green innovation on future corporate carbon emissions is that to a large extent green innovation has little to contribute to decarbonization. Where we see significant reductions in corporate carbon emissions, we find that these reductions are for the most part not due to green innovation. Overall, green innovation contributes only 1% to corporate carbon emission reductions. In sum, green innovation may be necessary for the sustainability revolution, but it is far from sufficient. The overwhelming conclusion of our analysis is that the green industrial revolution has not materialized over our sample period and the promise that green innovation will set the global economy on a sustainable path to net zero has not yet borne fruit.

Our paper contributes to a growing recent literature on the firm-level implications

of the transition to a green economy. A closely related study by Cohen, Gurun, and Nguyen (2022), who also look at green innovation by U.S. listed companies, draws somewhat different conclusions. They find that green innovation activity in the energy sector is higher than that in other sectors and conclude that this is evidence against path dependency of innovation. We confirm some of their cross-industry variation, but our main finding is that within each sector brown companies (those with higher emissions) do less green R&D. This is true across all sectors and countries. More specific differences are that we extend our sample to firms that also file for patents outside the USPTO, and to firms that are located outside the U.S. We further distinguish between green and brown efficiency patents, which allows us to evaluate the path-dependency hypothesis more explicitly. In this regard, we note that the classification of green patents used in their study tends to nest what we define as brown efficiency patents. Finally, their study takes ESG scores as a metric of environmental performance, which they motivate by the fact that asset managers tend to focus on such scores in their divestment screens. Our focus instead is on carbon emission outcomes.

A parallel literature in finance explores the effect of green innovation of U.S. firms on firm value (e.g. Hege, Pouget, and Zhang, 2022; Kuang and Liang, 2022; Reza and Wu, 2023). More broadly, Bolton and Kacperczyk (2021, 2023b) show that the transition risk, which embeds technological progress, is already reflected to a large extent in equity markets. Ilhan, Sautner, and Vilkov (2021) show that carbon risk is also priced in options. Engle, Giglio, Kelly, Lee, and Stroebel (2020) have constructed an index of climate news through textual analysis of the Wall Street Journal and other media and show how a dynamic portfolio strategy can be implemented that hedges transition risk with respect to climate change news. Sautner, Van Lent, Vilkov, and Zhang (2023) show that companies that report positive sentiment towards climate in their conference calls subsequently produce a greater number of green patents. In contrast to these studies, our focus is on the effects of green patents in decarbonization.

Earlier studies on rebound effects have focused on specific activities or on sector or country-level data. Our study is the first to explore the effects of technological change

on carbon emissions based on firm-level data.[3] The findings on rebound effects in this earlier literature are mixed. For example, Schipper and Grubb (2000) have looked at aggregate data on energy use and found that car use and energy use in other activities have not changed much in response to technological improvements in energy efficiency. Based on these findings they conclude that rebound effects are likely to be small. Sorrell, Dimitropoulos, and Sommerville (2009) provide a review of prior empirical studies on rebound effects. They argue that many studies only look at partial rebound effects over limited time periods and over restricted consumption responses. For example, studies on the consumption response to fuel-efficiency improvements in automobiles only measure changes in mileage travelled and do not consider more long-term changes in vehicle size. By looking at firm-level data and at cross-firm and cross-industry effects of green innovation we can identify substantially larger and more diverse forms of rebound effects.

The remainder of the paper is organized as follows. Section 2 provides the conceptual framing for our analysis. Section 3 describes the data and provides summary statistics. Section 4 discusses the results on the drivers of green innovation. Section 5 provides the results on the impact of innovation on future emissions and other corporate decisions. Section 6 concludes.

3.2 Conceptual Framework

We begin with a conceptual discussion of green innovation and the transition to a net-zero economy. There are three key guiding concepts that help us understand the various connections between green innovation and carbon emissions. The first, as already

[3] An important aspect of green innovation is the role of government policies in supporting innovation (for a literature review, see Greaker and Popp (2022)). These policies are important and can induce a shift to green innovation (e.g Popp, 2002; Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen, 2016). Our study focuses on firm-level responses and how they depend on their characteristics, especially their carbon emissions. We absorb the impact of innovation policies using industry and country fixed effects, making an implicit assumption here that innovation policies are industry-wide and not firm-specific. Our findings reveal how firms in an industry differentially respond to these policy interventions and how their differential response is linked to firm characteristics such as carbon emissions.

highlighted, is the Jevons paradox and other rebound effects of green innovation on energy consumption, one of which is the *displacement effect* defined above. The narrow notion of the Jevons paradox is that an energy efficiency gain, or a carbon intensity gain, from a better technology will of course reduce emissions for a given level of operations, but if the new technology invites more users and larger operations then the overall reduction may be limited or may not materialize at all.

We expect to find direct evidence of such a rebound effect if a brown efficiency innovation subsequently improves the carbon intensity of operations, but overall carbon emissions are not significantly affected or are higher. A general reason why one should expect a positive effect on operations and sales from a brown efficiency innovation is that the innovation improves profitability and the competitiveness of the innovating company, which are likely to result in an expansion of the business.

There are other, more indirect, and more subtle, displacement effects to be expected. A concrete and highly relevant example is the transition to electric vehicles (EV). This is one of the major new green innovations. If, as is likely to be the case, the share of EV grows significantly in the next few years then scope 1 emissions from transportation should be expected to decline. However, if the increased demand for electricity is met by increased production from coal-fired power plants, as is likely to be the case in states where coal-fired power plants are still responsible for the lion share of electricity production (such as West Virginia, with a 91% share, Missouri with 75%, Wyoming with 74%, and Kentucky with 71%)[4] , then the green EV revolution will result in an increase of scope 2 emissions. What does not get burned by the vehicle will get burned by the power company, with a likely net increase in total emissions given that coal is far more carbon intensive than oil. Similarly, the production of all the parts that go into an EV, from the wheels, tyres, chassis, body, engine, and batteries, etc, will generate carbon emissions, so that green innovation could also result in higher upstream scope 3 emissions. These higher emissions will be fully offset by lower scope 1 emissions than a combustion engine vehicle only after the EV has clocked up many thousands

[4]See https://www.eia.gov/todayinenergy/detail.php?id=54919

of miles.

Other rebound effects operate through product market competition. If green innovation involves higher costs than brown efficiency innovation (or no innovation), then the green innovating firm will be at a cost disadvantage relative to its industry peers. It may as a result lose market share. This would translate into lower carbon emissions for the green innovating firm, but higher carbon emissions for its competitors that are gaining market share. Alternatively, green innovation could spur adoption of green technologies by industry peers, leading to an industry-wide reduction in carbon emissions. In sum, green innovation is likely to have spillover effects, positive or negative, which could affect carbon emissions of non-innovating firms with the industry or across industries. To understand the overall impact of green innovation on carbon emissions it is therefore important to explore the link between green innovation activity and carbon emissions within and across industries.

The second and third guiding concepts for our analysis are closely related. They are both associated with founding ideas first proposed by Arrow (1962, 1971). One concept is commonly known as Arrow's replacement effect (Arrow, 1962), which refers to the idea that established firms, monopolies, have a lower incentive to innovate because their innovation mostly replaces their existing technology that is working and is profitable. The other concept, learning-by-doing (Arrow, 1971), has broader applications. But in the context of innovation, it means that companies understand the technologies they already use better, which induces them to continue to improve something they already master rather than explore new directions which seem more obscure. One key general prediction that follows from these two concepts is that profitable companies with operations based on fossil fuel energy (brown companies) are less likely to engage in green innovation, a new technology they are less familiar with, and less likely to replace their brown operations with green operations. A related general prediction is that innovation is likely to be path dependent: a company that has already been actively researching brown efficiency innovations is more likely to continue to do brown R&D. Green innovation, therefore is most likely to be undertaken by companies that

are new entrants.

Arrow (1962) focuses his analysis on an individual firm's technology and the replacement of the firm's own technology. When it comes to green and brown innovation, however, replacement has a broader scope and involves complementary technologies upstream and downstream. Replacement is not just confined to one firm. It may require technological changes in an entire ecosystem. Following the development of a new green technology an individual firm might be ready to replace its old technology if all the other firms it depends on also make the switch. A case in point is again electric vehicles. Switching to EV requires major changes not only in the supply chain but also downstream, with new charging station networks, maintenance, servicing, etc. Thus, the more dependent upstream and downstream industries are on fossil fuels, the less likely it is that an individual firm in one sector will transition to green technologies. A major general prediction that follows from this observation is that an individual company is less likely to do green R&D the higher are its upstream and downstream scope 3 emissions.

Finally, another key consideration in exploring the link between green innovation and future carbon emissions is the timing of deployment of new technologies. There can be a major time-to-build lag between the discovery and development of a new technology and its deployment. Part of this lag may be due to the time it takes to go from a working prototype to a mature technology. According to the latest research by the IEA (2020), many new green technologies in the energy sector are still at the prototype stage. Their impact on future carbon emission reductions is therefore likely to be small in the immediate future (see the IEA Figure 3.2).

Given the relatively short and finite time interval of our study, it is not possible to account for impacts that are far into the future. We cannot rule out the possibility that these impacts will be very large, and that green innovation will fully deliver on its promises. Still, it is important to find out whether, and the extent to which, green innovation is already having an impact on reducing carbon emissions, given the small

and rapidly shrinking remaining carbon budget, which according to the latest climate research is less than 300 gigatons (Gt) of CO2 as of 2020 if temperature rise is to be limited to less than 1.50C with an 83% probability (IPCC, 2021). Given that annual energy-related emissions have been around 31.5 GtCO2 in 2020 (IEA, 2021) and given that projected annual energy-related emissions for the next few years will remain at that level, there are only a few years left for green innovation to deliver on its promises before it is too late.

3.3 Data

Our data construction starts with all global firms, both publicly listed and private, identified between 2005 and 2020 in the following data bases: Orbis Intellectual Property Financial, Orbis, Factset, and Worldscope for financial information (balance sheets and income statements). The financial data for public firms is based on all four. The financial data for private firms is based solely on Orbis IP Financial and Orbis. The latter data sets only cover the ten most recent years. The overall dataset is termed "full sample". We merge these datasets with the Orbis Intellectual Property dataset, which provides a comprehensive coverage of patent filings and corporate ownership of patents by listed and unlisted companies in 81 countries. This dataset includes 136 million patents held by 2.3 million firms. It also provides patent citations, which are a good measure of the importance of the innovation protected by the patent. Henceforth, we refer to this dataset as the "patenting sample".

We further combine the full sample with data from Trucost on firm-level carbon and other greenhouse gas emissions. Trucost reports yearly firm-level carbon and greenhouse gas emissions data for scope 1, 2, and 3 emissions in units of tons of CO2 equivalent. Scope 1 emissions are direct emissions from operations of affiliates that are owned or controlled by the company. Scope 2 emissions are those that come from the generation of purchased heat, steam, and electricity used by the company. Scope 3 emissions are indirect emissions caused by the company's operations and the use of its

products. These include emissions from the production of purchased materials, product use, waste disposal, and outsourced activities. Establishing the scope 3 emissions of a company requires a detailed analysis of the share of emissions of producers in the supply chain that is attributable to the company's input purchases. This involves estimating an input-output model with sector-level emission factors. Our data allows us to distinguish between scope 3 emissions coming from upstream and downstream activities although the latter are only available from 2017 onwards; hence, total scope 3 emissions prior to 2017 reflect upstream emissions only. Finally, we include world index constituent data from MSCI. We use the ISIN identifier and company names to match these datasets.

3.3.1 Aggregate data by country

Internet Appendix Table B.I provides a breakdown of our aggregate data by country. In Panel A, we report a breakdown of the number of firms in each country that are respectively, publicly listed, privately held, and have carbon emissions data. The total number of firms in our sample is 788,983, of which 54,009 are publicly listed companies and 734,974 are privately held firms. There are 18,819 firms for which we have carbon emissions data through Trucost. The limited coverage reflects the fact that Trucost has collected emissions data mostly from listed and larger companies. Countries with the largest number of firms in the full sample include China, Italy, Denmark, and France, each of them having more than 50,000 companies in the full sample. Even excluding these countries, our sample has a wide cross-country representation. Notably, in the matched Trucost sample, the U.S. has the largest representation of all countries, which is consistent with the fact that it has the relatively larger fraction of publicly listed companies. In columns 5-8, we further restrict the full sample to observations for which we have patent data from Orbis. Throughout our main analysis, we focus on patents registered with the European Patent Office (EUPO). As is well known, the filing process is most rigorous at the EUPO, so that these filings reflect more signifi-

cant and enduring innovations. In the Appendix, we provide additional robustness results using patents registered with any patent office worldwide. The total number of firms in this subset of patenting firms represents roughly 3% of the universe of companies in our data, which reveals the fact that most companies do not get involved in any innovation activity. Interestingly, publicly listed patenting companies comprise about the same fraction of the sample with patents as privately held patenting firms. Still, private companies represent a significantly larger population of all firms. These numbers therefore indicate that public firms are significantly more likely to engage in innovative activities.

In Panel B we report the distribution of patent counts across countries. Most patents came from publicly listed companies, which provides further evidence that innovation is typically produced within large companies. Notably, the fraction of patents registered by companies that are part of the Trucost data is over 75%. The two countries with the highest number of patents in our sample are the United States and Japan, each one having more than 300,000 patents registered. The next three countries are Germany, France, and South Korea, each with more than 100,000 patents. In columns 5-8, we show the average number of patents per firm, for companies that do engage in patenting activity. An average company in our sample registered more than 17 patents over the sample period. The fraction is significantly larger for public firms, which register more than 24 patents per firm in contrast to private firms where this number is 5.7.

Table B.II further shows the country-level breakdown into firm-year observations. To be included in the final sample, we require firm-year observations to have values for assets, book leverage, ROE, and country of incorporation. We lose about 3,700,000 firm-year observations due to this restriction. In addition, we require public firms to have records for capex, previous year's December return, volatility, and market capitalization. This leads to another 200,000 firm-year observations being lost. In the paper, we refer to this filtered dataset with 5.3 million firm-year observations as the "full sample". Columns 1-4 present the numbers for the full set of public and pri-

vate companies. The number of observations in the full sample is 5,318,818, of which 390,985 are observations from public firms and 4,927,833 are observations from private firms. In columns 5-8, we restrict the sample to companies with at least one listed patent. That sample includes 88,727 observations, 63% of which are from publicly listed companies.

3.3.2 Green and brown innovation

We make a key distinction between *green innovation*, targeting technologies that substitute carbon dioxide emitting technologies for carbon dioxide-free technologies (or that make carbon-dioxide-free technologies more accessible), and *brown innovation*, which targets improvements in fossil-fuel based technologies. For this patent classification we rely on the description of the patent and four technology classification sources on patents relating to the environmental impact of technologies, namely the environmental technologies classified by the Organization of Economic Co-operation and Development (OECD)[5], the International Patent Classification (IPC) Green Inventory[6], the efficiency-improving fossil fuel-technology categories of Lanzi, Verdolini, and Haščič (2011), as well as a self-identified classification based on patents from the Corporate Knights Clean 200. We classify patents into three broad categories[7]: i) green patents for environmental technologies; ii) general efficiency improvement patents that deal with technologies that improve process efficiency and therefore could reduce emission intensity; iii) brown patents that deal with technological innovation for fossil fuel-based technologies. For robustness, we also consider the OECD classification of green patents, which includes technologies related to environmental applications, such as climate mitigation, biodiversity, and wastewater management, as well as green and general efficiency improvements patents.

Prior research (e.g. Cohen, Gurun, and Nguyen, 2022; Aghion, Dechezleprêtre, He-

[5]https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm
[6]https://www.wipo.int/classifications/ipc/green-inventory/home
[7]We provide a detailed description of our approach and the underlying IPC/ CPC classes here

mous, Martin, and Van Reenen, 2016) has relied on the OECD classification of green patents only. But the OECD classification does not always distinguish between patents on renewable energy technologies and brown efficiency improvement patents. Some green patents within the OECD classification are brown efficiency patents. To illustrate this point, we conduct a cloud-of-words analysis of patent descriptions using the term frequency–inverse document frequency (TFIDF) algorithm. We search for the dominant words in our green patent classifier, stripping out common words in the OECD classification, and we do the same for the OECD classification, searching for the dominant words and stripping out the common words from our classification. We present the resulting clouds in Figure 3.3.

In the left figure, we show the words that are uniquely dominant to our classification. Words, such as mri, magnetoresistive, or magnetometer are very common to fusion reactions and underlie the green nature of the patent. In the right figure, we start with the OECD words and filter out common words from our classification. The dominant words of this process include exhaust gas, internal combustion, or abradable, all three likely attributed to efficiency gains of brown technology. Overall, this analysis suggests that our classification is more accurate in identifying purely green patents. The OECD classification misclassifies some patents as green when they are more likely to be brown patents. For the rest of the analysis, we will thus rely on our classification, but we also check the robustness of our findings to using the OECD classification.

In Table B.III, we report the distribution of firms and patents conditional on a firm filing a green or brown patent. In Panel A, we analyze the distribution of firms by country. In columns 1-4, we report the statistics for firms which file a green patent, and in columns 5-8 the statistics for firms which file a brown patent. Only about 1% (0.4%) of all firms have at least one green (brown) patent. In the cross-section, the U.S., Japan, and Germany (the U.S., Japan, and China) have the largest number of firms with green (brown) patents, each of them representing 7%-20% (7%-28%) of the total number of patenting firms. The distribution of countries contributing at least one green (brown) patent is skewed, with the top 10 countries contributing most green

(brown) patents. Publicly listed companies account for 63% (66%) of firms with green (brown) patents. The fraction of firms with at least one green (brown) patent that is covered by Trucost is roughly 42% (48%).

In Panel B, we provide a similar breakdown for the total and average (per firm) number of green patents. In the full sample, over the period 2005-2020, companies have filed 162,039 green patents. In this group, a large number (144,614) of green patents is registered with publicly listed companies, and only 17,368 patents are registered with private companies. More than 131,000 of green patents have been filed by companies with emission data in Trucost. The highest number of green patents by firm comes from Saudi Arabia, South Korea, and Germany, each of them having more than 10 patents per firm. In Panel C, we provide a similar breakdown for brown patents. In the full sample, we observe 63,689 brown patents in total; 56,556 of those patents have been filed by publicly listed companies and the remaining 7131 are those filed by private companies. Saudi Arabia, Germany, and the United Kingdom are the three countries with the highest number of brown patents per firm.

In Figure 3.1, Panel A we show the year-by-year distribution of patenting activity, measured by green and brown patent counts, based on the sample of all firms with patent data. We observe a steady increase in patenting activity over time at least until 2018, especially for green patents. Green patents also represent a larger share of patenting activity. We also separate the data into different regions. The two regions with the largest number of either green or brown patents are Asia and Europe. At the peak of 2018, each region contributed almost 10,000 patents each. The equivalent number for North America is significantly less and accounts for about 5,000 patents. Notably, countries outside these three regions, which include Africa, Australia, and South America, contribute almost no patents to the overall patent count. This fact underlies the importance of any innovation spillovers from patenting to non-patenting regions, especially because these non-patenting regions are responsible for significant fraction of global emissions. Panel B presents observations for all firms that are available in Trucost. The subsample quite closely mimics the behavior of the unconditional

sample. We observe a steady increase in observations from 2005 until 2015. More pronounced is the sharp increase in observations starting from 2016. This increase can be largely explained by the change in firm coverage by Trucost that took place post-Paris agreement. This can be better observed in Panel C, in which we restrict our observations to firms that are featured in Trucost prior to 2016. We still observe the increase in firm observations over time but the sharp increase in 2016 is no longer as pronounced.

3.3.3 Innovation Capacity: scale & scope

The summary statistics in Section 3.1 suggest that the probability of a firm filing a patent is skewed towards larger firms. This result is not entirely surprising. To be able to innovate firms need to build research teams, laboratories, and other facilities. It is to be expected that bigger firms can build bigger research facilities, and therefore can produce more patents. What is more, firms are more likely to continue incurring these fixed costs if their innovative activities have been successful. And so, a plausible hypothesis is that the past stock of patents along with the size of the firm predict future patenting activity. If firms' innovation capacities are limited by their size, one would also expect to see some substitution between different R&D directions. Not all promising research and development projects can be pursued at the same time. Firms choose the projects that show the greatest promise given their state of knowledge and know-how. Thus, another plausible hypothesis is that firms specialize in the R&D they become good at.

We begin our analysis by formally exploring these two hypotheses. First, we associate a firm's number of new patent filings at the European patent office in year t (ANYCOUNTEP) with its stock of European patents up to year t (PASTSTOCKANYEP), its size, number of employees, assets, and its age, using a Poisson pseudo-maximum likelihood model (which allows for non-trivial numbers of zeros in dependent variables). We report our findings in Table 3.1, Panel A. In columns 1 to 3, we look at the extensive margin by including all firms, whether they have any patents or not. In

columns 4 to 6, we look at the intensive margin, by including only firms that have engaged in innovation activities in the past and own some patents. Specifications 1 and 4 include country and year fixed effects, specifications 2 and 5 additionally include industry-year fixed effects, and specifications 3 and 6 use firm fixed effects instead of industry-year fixed effects. In all models, we double cluster standard errors at the firm and year dimensions to allow for cross-correlation and serial correlation of residuals.

Consistent with our first hypothesis, we find that the stock of patents already owned prior to year t (PATSTOCKANYEP), the age of the company, and the three measures of firm size (market cap, number of employees and total assets), all positively predict future patenting activity when we add industry-year fixed effects. This is true both at the extensive and intensive margins. In other words, innovative activities of firms are constrained by their innovative capacity, which is greater for larger firms and for firms that have greater R&D experience (as reflected in the patent stock and firm age variables). As others have pointed out (e.g., Acs and Audretsch 1988, 1991), much innovation activity takes place at large companies. Our findings confirm these observations (albeit based on broader and more recent data). These results provide important context for our other findings below on the path-dependency of R&D activity.

In Panel B of Table 3.1 we turn to our second hypothesis, specialization through learning-by-doing. Here we distinguish between the number of green patents a firm files in year t (GREENCOUNTEP) in columns 1 to 3, and the number of brown patents (BROWNEFFCOUNTEP) it files, in columns 4 to 6. We also break down the patent stock variable into the stock of green patents (PATSTOCKGREENEP) the firm holds up to year t, and the stock of brown patents (PATSTOCKBROWNEFFEP). Consistent with our hypothesis, we find strong evidence of specialization, with a higher stock of green patents (resp. brown patents) positively predicting future green innovation activity (resp. brown innovation activity). Moreover, a higher stock of green patents (resp. brown patents) negatively predicts future brown innovation activity (resp. green innovation activity). This latter finding in particular reveals both the presence of scope constraints for innovation and the effects of learning-by-doing. Overall, this lat-

ter finding uncovers strong path-dependency for innovation: greater experience with brown technology reduces the likelihood of future green innovation activity; similarly, greater experience with green technology reduces the likelihood of future brown efficiency innovation. This evidence is consistent with the path-dependency findings of Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen (2016) for the auto industry. Path dependency is not just a feature of that industry. It extends across industries and around the world.

3.3.4 Green and brown innovation ratios

As we have shown, patenting activity in any given year is significantly driven by a firm's innovation capacity. Moreover, the different directions in which a firm can pursue R&D are constrained by the firm's innovation capacity, so that there is some substitution between different R&D directions. Accordingly, new patent filings must be related to the firm's innovation capacity to get a more accurate picture of the intensive margin of innovation activity. For that reason, we normalize the number of green (respectively brown) patent filings by the total number of patent filings and define the following two variables: GREENRATIOEP is the ratio of green patents filed at EUPO over the total number of patent filings in that year; BROWNEFFRATIOEP is the ratio of brown patents filed at EUPO over the total number of patent filings in that year.

Table B.IV, Panel A provides information on the ratios of green or brown patent filings for each country. In columns 1-4 we focus on green patent ratios. The average green patent ratio equals approximately 11%. Interestingly, the ratios do not differ greatly between publicly listed and private companies, with the former having an average ratio of 11.4% and the latter 10.3%. For the Trucost sample, the numbers are slightly higher. Furthermore, innovation activity (as measured by the number of firms with at least one patent) is proportional to the size of the economy. Among the countries with more than 300 public or private companies, some of the ones with the highest ratios of green to total number of patents are: Norway with a ratio of 16.4%, Canada with a

ratio of 15%, and Denmark with a ratio of 14.5%. In comparison China has a ratio of 12.9%, and the U.S. an even lower ratio of 10%. Notably, Saudi Arabia reports a large fraction of green patents 14.9%, and the UAE an even higher ratio of 23.5%, which is interesting given their strong reliance on oil production. In columns 5-8 we provide respective summary statistics for brown patents. On average, brown patent ratios are significantly smaller. The average number for the EUPO patents equals 3.33%. The unconditional numbers do not deviate much from those based on the Trucost sample. Notable countries for significant brown patenting activity include Malaysia, Australia, India, Greece, Singapore, and the U.K. The numbers for the U.S. and China are about the same 2.61%.

Panel B breaks patent activity down by sector (GICS6-industry). In columns 1-4 we present the results for green patents. Some sectors stand out for the intensity of their innovation activities. The Independent Power and Renewable Electricity Producers industry has the highest ratio of green patents filed at EUPO, with 53.78%, followed by Electric Utilities, Multi-Utilities, and Gas Utilities. These results are broadly consistent with those in Cohen, Gurun, and Nguyen (2022) for the U.S. On the other end of the green R&D spectrum, IT and healthcare sectors are the two industry groups with the lowest green patent ratios. The ratios are broadly within the same range for public and private firms. They are also not markedly different when we restrict our sample to Trucost observations, which is reassuring about any selection concerns one might have. In columns 5-8 we report the results for brown patents. The ratios are generally larger for publicly listed firms, especially in those sectors with higher ratios. Among the most active industries, Energy Equipment & Services leads with the highest ratio of 19.95%, followed by Automobiles at 14.38%, and Independent Power and Renewable Electricity Producers at 12.5%.

In Panel C, we report the distribution of patenting activity by year, with columns 1-4 providing green patenting activity over time and columns 5-8 providing brown patenting activity. Green patent ratios have steadily increased over time. For example, in column 1 we see that this ratio was below the average of 11% in 2005, with a ratio 8%,

but above average in 2020 with a ratio of 12.9%. The same increasing trend in green patent activity can be observed for listed companies (in column 2), private companies (column 3), and for Trucost companies, which are mostly listed companies (in column 4). When it comes to brown patent filings, we see the opposite trend and a decline in R&D activity over time for brown technologies, but the rate of reduction is very small. In Figure 3.4 we plot the patent ratios across time by region and find broadly similar patterns.

3.3.5 Summary Statistics

In this section we provide summary statistics for the main variables in our models, conditional on whether firms file patents. In addition, we report complete summary statistics for publicly listed firms with carbon emissions data (those that can be matched to the Trucost dataset). Our empirical analysis in the subsequent sections is based on this restricted sample. Accordingly, these summary statistics provide information on how the broader universe of firms may differ from the Trucost universe.

We begin by defining all the variables. Our first category is variables related to innovation activity. Besides the variables measuring general innovation activity and respectively green innovation, and brown efficiency improvements that we defined above, we also include variables measuring the impact of patents by how widely cited they are. GREENRATIOEP2 is defined as the number of granted or purchased "green" or "general efficiency" patents over the total number of granted or purchased patents; OECDRATIOEP is a patent ratio based on OECD green Env-tech classification, calculated as the number of granted or purchased OECD patents over the total number of granted or purchased patents; GREENCITMAXEP (BROWNEFFCITMAXEP) is the maximum number of forward citations any green (brown) patent of a firm received; GREENBBCOUNTEP (BROWNEFFBBCOUNTEP) is the number of green (brown) blockbuster patents patent per firm, where blockbuster patents are defined as patents in the 95th percentile based on the number of forward citations in a given

grant year and classification.[8]

In our second category we include variables measuring corporate carbon emissions (direct and indirect) when available, and standard variables capturing key corporate characteristics.[9] Thus, LOGS1TOT, LOGS2TOT, LOGS3TOT, LOGS3UPTOT, and LOGS3DOWNTOT respectively stand for the natural logarithm of firm-level scope 1, 2, and 3 (also upstream and downstream) total carbon emissions, and S1INT, S2INT, S3INT, S3UPINT, and S3DOWNINT are firm-level scope 1, 2, and 3 emission intensity variables defined as the level of emission divided by firm sales. In our third category we include the main variables reflecting key corporate characteristics: i) LOGSIZE stands for the natural logarithm of a listed company's market capitalization (price times shares outstanding); ii) LOGPPE is given by the natural logarithm, of the firm's property, plant, and equipment (in $ million); iii) LEVERAGE is the ratio of debt to book value of assets; iv) ROE is given by the ratio of firm i's net yearly income divided by the value of its equity; v) M/B is the end of year market cap divided by the firm's book value; vi) BETA is the market beta of individual companies calculated over the preceding 12-month period; vii) VOLAT is the standard deviation of returns based on the past 12 monthly returns; viii) momentum, MOM is given by the average of the most recent 12 months' returns on stock i, leading up to and including month t-1; ix) short-term reversal, RET is the past year's December return on stock i; x) capital expenditure INVEST/A is the firm's capital expenditures divided by the book value of its assets; xi) MSCI is an indicator variable equal to one if a stock is part of the MSCI ACWI index in year t, and zero otherwise; xii) LOGCAPEX is the natural logarithm of firm-level capital expenditures; and xiii) LOGCASH is the natural logarithm of firm-level cash positions. To mitigate the impact of outliers we winsorize M/B,

[8] Measuring the importance of patent value is generally a challenging question and, in this paper, we rely on the most basic measure of citation, particularly because of our global focus in the paper. Kogan et al. (2017) is an excellent study providing a more detailed discussion of these issues.

[9] Note that we do not have a complete coverage of all corporate emissions. The Trucost data covers around 85% of listed companies worldwide, and almost no privately held companies. The numbers we report are therefore an underestimate of total corporate emissions, and since a growing fraction of high emitting companies (or their affiliates) have delisted over the period we cover, this underestimate is likely to be larger in later years.

LEVERAGE, INVEST/A, and ROE at the 2.5% level, and MOM and VOLAT at the 0.5% level.

In Table B.V we report the sample averages, medians, and standard deviations of these variables. Panel A is based on all public and private firms, and Panel B on firms with available emission data. Columns 1 to 3 aggregate all firms with at least one patent. Columns 4 to 6 aggregate firms without any patents. Columns 7 to 9 aggregate firms in the bottom decile based on firms' average GREENRATIOEP across the whole period. The bottom decile covers only firms with no green patents and represents around 35% of observations. Columns 10 to 12 aggregate firms in the top decile based on firms' average GREENRATIOEP across the whole period. Both Panels A and B reveal considerable heterogeneity in innovative activity. Among the firms that hold at least one patent, there is a wide dispersion in green innovation as reflected in the standard deviation of GREENRATIOEP of 26.08% and the standard deviation of GREENCITMAXEP of 155.89. Interestingly, the average level of emissions of innovating firms is significantly larger than that of non-innovating firms, with the mean of LOGS1TOT equal to 6.13 for innovating firms but only 4.85 for non-innovating firms. A similar difference holds for scope 2 and 3 emissions. Partly this difference could be attributed to the fact that innovating firms are slightly larger (mean LOGSIZE is 7.86 for innovating firms versus 6.93 for non-innovating firms). Patenting firms have also greater values of LOGPPE, LOGCAPEX, and LOGCASH, and slightly higher values of M/B than non-patenting firms do. At the same time, they do not differ much in terms of their BETA, VOLAT, MOM, and INVEST/A. Notably, we observe similar relationships for variables that are observed for the full and restricted samples, which suggests that the relationships we identify based on our restricted samples are not less likely driven by specific selections along different observables.

We now turn to the analysis of innovation and the carbon transition. Our analysis will be guided by three fundamental insights, the *Arrow replacement effect* (Arrow, 1962), *Jevons' paradox* (Jevons, 1865), and the *displacement effect*. Arrow (1962) has pointed out that "The pre-invention monopoly power acts as a strong disincentive to further

innovation."[10] More generally, the incentive to innovate is reduced if the innovation replaces an existing technology that is working and is profitable. By that principle one should expect companies that master technologies based on fossil fuels to be less motivated to engage in green innovation that would replace a technology and know-how that is already working. This is even more likely if green innovation involves retooling and abandoning a knowledge base around fossil fuel-based technology. If there is an incentive to innovate for an incumbent firm with a fossil fuel-dependent installed base it is more likely to take the form of efficiency improvements in the use of fossil fuels, what we refer to as *brown efficiency improvements*. Indeed, this innovative activity plays into the strengths of the incumbent firm, its expertise with brown technologies, which it has built through learning by doing (Arrow, 1971).

Carbon emissions can be reduced by replacing brown with green energy or by improving the carbon efficiency of brown energy. Thus, both green and brown efficiency innovations are central to the drive to decarbonize the economy. But, as Jevons (1865) has pointed out, brown efficiency improvements do not necessarily translate into carbon emission reductions because the very efficiency gain is also inviting greater use. Furthermore, the displacement effect from green innovation may displace scope 1 emissions to scope 2 and scope 3 emissions, as is for example the case for electric vehicles.

In the next section we explore how green innovation activity is shaped by Arrow's replacement effect. In the following section we turn to Jevons' paradox and the displacement effect to explore the link between green innovation and the future decarbonization of the economy.

[10] Kenneth Arrow "Economic Welfare and the Allocation of Resources for Invention," page 620, in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, NBER.

3.4 Green Innovation Activity: Arrow's replacement effect and path-dependent innovation

Basic economic analysis would suggest that firms engage in green R&D if it is more profitable than both no R&D and other R&D. Another consideration is comparative advantage—some firms, such as renewable energy companies, may be both better equipped and benefit more from green R&D. Brown companies that rely on fossil fuel energy may be better at squeezing out efficiency gains in brown technologies. Alternatively, "khaki" R&D, that is, green innovation by brown companies, may be most profitable if fossil fuel energy is increasingly regulated and expected to become obsolete. We explore these hypotheses in this section and point to some key factors driving green R&D across sectors and around the world. Overall, the picture that emerges is the importance of path-dependency in understanding green innovation activity at the firm level. As we will show, green firms (that are already familiar with green technologies) are more likely to produce green patents, whereas brown firms (which have expertise in fossil fuel-dependent technologies) are more likely to produce brown patents. Similarly, older companies (the industry incumbents) are more likely to engage in brown efficiency innovation, while younger companies (the new entrants) are more likely to engage in green innovation. We also find that a key predictor of patenting activity is the stock of past patents that a company holds. Companies that have been successful innovators in the past have capacities that allow them to continue to innovate. However, as we have shown, innovation capacities are limited. Companies cannot innovate in all promising directions. If their past innovative activities tended to be specialized in brown efficiency innovations, they will continue to innovate in that direction. In sum, innovation activity is characterized by path-dependence consistent with the findings of Popp (2002) and Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen (2016).

3.4.1 Green vs Brown Innovation: Firm type and Path-dependency

The sustainable energy technological revolution necessarily involves substituting fossil fuel-based technology for green technology. Is this substitution taking place within firms (with the greening of brown firms) or across firms (with the replacement of brown firms by green firms)? This is the question we explore in this section.

Our working definition of a *brown* firm is a firm with high carbon emissions, that is older, may have larger assets, and may be a value company. Similarly, a *green* firm is one that has low carbon emissions, is younger, may have smaller asset size, and may be a growth firm. These characteristics are not the only possible ways to define a firm type, these are more to illustrate the point that companies' emissions may be systematically driven by some ex-ante metrics. As the histograms in Figure 3.5 show, our green vs brown firm type classification is broadly descriptive of our universe of companies. Each panel shows the distribution of scope 1 emissions for companies in the lowest and the highest quintile of the distribution that is conditional on three different characteristics. In Panel A we show how younger firms (in the bottom quintile) have a distribution of scope 1 emissions that is skewed towards lower levels than the distribution for older firms (in the top quintile). Similarly, in Panels B and C we show that firms with respectively larger asset size and larger M/B ratios have also lower means and medians of their emissions.

Our question, rephrased with reference to these two firm types, then will be the extent to which we see green innovation activity at green versus brown firms, and whether we see brown firms greening themselves through green R&D. Given that firms have limited innovation capacities and given that the research projects that are most promising in view of individual firms' accumulated know-how tend to crowd out other R&D, it is natural to measure the amount of green (resp. brown efficiency) R&D in terms of the ratio of green-to-total patent filings (resp. brown efficiency-to-total patent filings).

How are green (resp. brown) patent ratios linked to firm type, specifically the firm's

corporate carbon emissions, its age, and green and brown patent stocks? To answer this question, we estimate the following Pseudo Poisson Maximum Likelihood model with firm (i) and year (t) as units of observation[11]:

$$Patent\ Ratio_{i,t} = a + b * Firm\ Type_{i,t-1} + c * Controls_{i,t-1} + FixedEffects + \epsilon_{i,t} \quad (3.1)$$

where *Patent Ratio* is a generic variable that allows for different types of patents to be related to the total number of patent filings. *Firm Type* (a continuous variable measuring the share of a firm's green and brown activities) is proxied by a combination of i) LOGS1TOT (and other carbon emission variables); ii) PATSTOCKGREENEP and PATSTOCKBROWNEFFEP, and iii) AGE/100. *Controls* is a vector of the following variables: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. We include country and year fixed effects. In some specifications, we also include industry-year or firm fixed effects. Our baseline specification uses the Trucost sector classification of 431 industries. To allow for the cross-sectional and serial dependence in the residuals we double cluster standard errors at the firm and year dimensions. Our coefficient of primary interest is b.

We report our findings for the extensive margin (which includes all firms, whether they own any green, respectively brown, patents or not) in Table 3.2. In columns 1-3, we present the results for green innovation activity (GREENRATIOEP), and in columns 4-6 the results for brown innovation activity (BROWNEFFRATIOEP). When industry fixed effects are not included (column 1) the coefficients of LOGS1TOT and PATSTOCKGREENEP are positive and statistically significant. The coefficient of AGE is negative and statistically significant. Not controlling for industry, however, is misleading because technological differences (and differences in emissions) across industries are huge. The results of the regressions without industry fixed effects are therefore difficult to interpret. For this reason, we consider specifications that absorb the time-varying differences across industries through industry-year fixed effects.

[11] Since many companies do not report any green patents a standard OLS regression is not suitable to estimate this relationship.

When industry-year fixed effects are included (column 2) the coefficient of LOGS1TOT is highly significant and negative. The other two coefficients retain the same sign and significance as before. When we further include firm-fixed effects, in column 3, the coefficients of LOGS1TOT and PATSTOCKGREENEP become insignificant.[12] The results flip when we look at brown innovation activity (BROWNEFFRATIOEP) in columns 4-6. For this type of innovation activity, the association with direct carbon emissions is strongly positive across firms within the same industry (when we include firm fixed effects, in column 6, the association for LOGS1TOT becomes negative, suggesting that when direct emissions increase firms tend to reduce their innovation activity). Overall, the combination of these results has a clear interpretation: green companies do more R&D that is green, and brown companies do less; instead, the latter do more brown R&D. What is more, these are cross-firm rather than within-firm effects (when we substitute industry*year FE for firm FE neither the coefficients for carbon emissions nor for the stock of patents are significant). These results further confirm the path-dependency hypothesis for R&D. To the extent that brown companies engage in innovation activities, their innovations are less likely to be directed towards green patents (and the opposite is true for green companies). In addition, green innovation is most likely to be undertaken by new entrants. Incumbents, far from embracing renewable energy technological change, respond by seeking to improve the efficiency of fossil fuel-based technology. The auto industry provides a good illustration of these findings. Indeed, the EV revolution has been driven by new entrants (Tesla, BYD) and incumbents have responded by improving the carbon efficiency of their vehicles.

In Table B.XI, we further explore the link between green innovation and direct carbon emissions on the *intensive margin*. That is, we restrict the sample to the universe of firms that have engaged in innovation (all the firm-year observations with at least one green patent, in columns 1 to 3, and/or one brown patent, in columns 4 to 6) and explore how the intensity of green (respectively brown) innovative activity is related to the stock of respectively green and brown efficiency patents the firm already owns,

[12] In the specification with firm-fixed effects we cannot uniquely identify the coefficient of AGE because its variation is collinear with that of firm and year fixed effects.

firm age, and the firm's direct carbon emissions. The empirical model follows that in Table 2, and it is estimated using OLS with standard errors double clustered at firm and year dimensions. Our findings for the intensive margin are broadly consistent with those for the extensive margin. If anything, they are stronger, except for firm age and scope 1 emissions, which are no longer significant for brown efficiency innovation, suggesting that entry and exit play a more important role in the relationship between the variables in the data.

Patent counts (or patent ratios) are somewhat coarse innovation performance metrics to the extent that many patents have limited applications. Accordingly, we also take patent citations (which reflect the importance of a patent) as an additional measure of innovation activity. In Table 3.4, Panel A, we associate the citation number of the patent with the maximum citations (respectively our GREENCITMAX and BROWNEFFCITMAX variables) with the same firm characteristics as in our previous regression for the green and brown patent ratios. We find very similar qualitative effects. Companies with higher emissions have lower citations for their green patents but higher citations for their brown patents. Also, companies with a greater stock of green (brown) patents are more likely to receive more citations of their green (brown) patents. Notably, firm age is positively associated with citations of both types of patents. This is to be expected since citations generally take time to accumulate. Similarly, our findings on the path-dependency of green R&D are confirmed when we focus on the most important new patents by citation count, GREENBBCOUNTEP and BROWNEFFBBCOUNTEP, in Panel B. Companies with a higher stock of green patents are more likely to make further important green innovations, and companies with a higher stock of brown patents are more likely to make additional brown efficiency innovations. The results for firm emissions and age are slightly weaker.

We find more direct evidence of Arrow's replacement effect at work in Table 3.5, where we explore how the firm's market share affects the path-dependence of innovation. If the replacement effect is at work, we would expect to see firms with larger market share do less green innovation other things equal. In Table 3.5 we explore how a firm's

market share based on its sales relative to total public and private firms' sales in the same Trucost sector (MKTSHRSALES TRUIND) affects its green innovation activity. Strikingly, we find that firms with a larger market share do significantly less green innovation, but they do more brown innovation. Note that when we replace industry*year FE with firm FE market share is no longer a significant variable, so that this effect is entirely driven by selection in the industry. An additional prediction of the model is that firms with greater market share should be in a better position to switch their innovation profile because of their stronger competitive position. To test this hypothesis, we interact the firms' market share with their type (measured by scope 1 emissions, firm age, and the stock of green and brown efficiency patents). In the model in column 2 that accounts for industry-year fixed effects, we find that green innovation is less path dependent when firms have a larger market share. This result holds for all three measures of firm type. The results based on brown innovation are similar for firm type measured by scope 1 emissions but are weaker when we measure firm type with the stock of brown patents, or firm age. Note that the interaction effect is again driven by selection in the industry. Indeed, when we replace industry*year FE with firm FE we find that a higher stock of green patents induces more green innovation (and a higher stock of brown patents induces more brown efficiency innovation). These findings are all consistent with Arrow's replacement effect: more entrenched firms (as measured by their market share) have lower incentives to do R&D and they are also more likely to switch their type because of their greater flexibility to do so.

Our findings so far are that brown companies (with higher direct emissions) do not tend to engage in green R&D. This may be due to replacement and/or learning-by-doing effects. Another possibility is that brown companies may be locked into fossil-fuel dependent technologies through their production networks. If input suppliers or downstream firms/customers also rely on fossil fuel-dependent technologies, then an individual firm in the supply chain may not be able to easily switch to green technologies. We investigate the presence of such technological complementarities across firms by exploring whether indirect (scope 2, upstream and downstream scope 3) emissions

are linked to corporate green R&D. We report the findings of this analysis in Table 3.6. It is indeed the case that the technological ecosystem in which a firm operates affects its incentives to engage in green R&D. As can be seen in columns 1, 2, and 3 of Panel A, the higher are the firms' indirect levels of emissions along the vertical production chain the less likely the firm is to engage in green R&D. Also (as is shown in Panel B), when it comes to brown efficiency innovation, the higher are firms' upstream scope 3 emissions the stronger are their brown innovation activities. Similar, but slightly weaker results hold for scope 2 and downstream scope 3 emissions. All in all, these latter findings reveal the presence of a much broader replacement effect than the firm-specific replacement effect identified by Arrow (1962): Replacing an old technology with a new one is more costly and less profitable if other firms along the supply chain do not follow in making the switch. This key finding suggests that in order to induce firms to transition from brown to green technologies, industrial policy that helps coordinate this transition across all firms linked through the supply chain may be needed.

We also explore the change in path dependency of R&D over time in response to the rise in climate change awareness and tighter mitigation policy responses following the Paris 2015 landmark agreement. We split our sample into two subperiods, before and after 2015. We report our results in Table 3.7. The results in Panel A are for the full sample, and those in Panel B are only for the legacy sample (the firms for which we have carbon emissions data before 2015). The interactions LOGS1TOT*Post2015, AGE*Post2015, and PATSTOCKGREENEP*Post2015 (resp. PATSTOCKBROWNEP*Post2015) capture the change in path-dependency around the Paris agreement (where Post2015 is an indicator variable taking the value 0 for all observations before 2015 and 1 after 2015). Interestingly, there is no significant change in the link between carbon emissions and green (or brown) patent activity. However, the stock of green patents matters more for future green R&D post 2015, suggesting that green R&D has become more valuable post 2015 and is pursued by the (new entrant) green firms.

3.4.2 Robustness

We perform several robustness tests and report the findings in the Appendix. In Tables B.VI and B.VII we report the findings of our main regression analysis industry by industry for each GICS6 industry to better understand in which industries our results are strongest. Overall, path-dependency results are found in most industries, especially for the regressions with green patents as dependent variable.

Second, we explore how sensitive our path-dependency results are to different patent classifications. In Table B.XI we replace our green patent classification with the broader OECD classification of green patents, which includes more general technologies related to environmental applications, biodiversity, and wastewater management, as well as a green classification capturing both green and general efficiency patents. We find that the qualitative predictions uncovered for our green patent classification also hold for this broader green classification. Firms with higher emissions, that are older, larger, and have a smaller stock of green patents do less green R&D.

Third, we explore the sensitivity of our results to different patent filings than European patent office filings. In Table B.IX we count all patent filings anywhere in the world. The dependent variables now are the ratio of green to total worldwide patent filings in year t (GREENRATIOWW in columns 1 to 3) and the ratio of brown to total worldwide patent filings (BROWNEFFRATIOWW in columns 4 to 6). Similarly, the stock of patents (PATSTOCKGREENWW and PATSTOCKBROWNEFFWW) now includes all patents filed anywhere in the world. The results clearly show that the qualitative results on path dependency also obtain when we look at the noisier measure of patent activity based on worldwide filings.

Fourth, we revisit the results of Table 3.2, using two alternative definitions of industry, based on 6-digit and 8-digit GICS scores. We report the results in Table B.X. We find that qualitatively changes in industry classification do not affect our results on path dependence. Another robustness test we conduct is to restrict our sample to

those firms for which we have carbon emissions data before 2015 (our legacy sample). Again, as reported in Panel A of Table B.XI (for the extensive margin) and Panel B of Table B.XI (for the intensive margin), our qualitative results are unchanged. We also explore how much mergers and acquisitions affect our findings. In Table B.XII we report the findings of our regressions based on a sample that excludes all companies engaged in mergers and acquisitions (M&A) over our sample period. The results are qualitatively similar to our baseline findings. M&A activity is largely orthogonal to the determinants of corporate innovation activity even if some acquisitions are motivated by access to innovation.

We also explore how green innovation is distributed across firms by the size of their carbon emissions. In Table B.XIII, we report the findings when we split our sample into terciles based on firms' initial scope 1 emissions (the first year when we observe a firm's scope 1 emissions). In Panel A the dependent variable is the green patent ratio and in Panel B the dependent variable is the brown efficiency ratio. Interestingly, the most significant negative effects of carbon emissions on green innovation are concentrated in the tercile of firms with the lowest emissions. But the stock of green patents has similar predictive effects on green innovation across all three terciles. In contrast, the most significant effects of carbon emissions on brown innovation are concentrated in the tercile of firms with the largest emissions. Again, however, the stock of brown patents has similar predictive effects on brown efficiency innovation across all three terciles.

3.5 The effects of innovation on future carbon emissions

We have shown that green and brown efficiency innovation is strongly path dependent. Green companies (which tend to be younger) are more likely to produce green patents, while brown companies are more likely to produce brown efficiency patents. That is, brown companies do not redirect their innovation towards green innovations. Rather, they focus on squeezing out efficiency gains in their brown operations. These

results suggest that companies are unlikely to decarbonize through the switch of their innovation profiles.

In this section we systematically evaluate the effects of (green and brown) innovation on future carbon emission reductions. Much is predicated on the assumption that technological change is the solution to the climate crisis. But do green and brown efficiency innovation significantly reduce carbon emissions? The archetypal image of a technological change that drastically reduces carbon emissions is the substitution of a coal-fired power plant by a photovoltaic power station, or the substitution of a combustion-engine car by an electric vehicle. Yet even these obvious examples come with questions about the net effects of these technological changes on carbon emissions, since solar panel and electric vehicle production require inputs and use energy that causes upstream and downstream carbon emissions, giving rise to the displacement effects. Similarly, with brown efficiency-improving innovation the effect on carbon emission reductions may be limited because of rebound effects. Fuel economy innovations for combustion engine cars may be undone by people driving longer distances. Battery life improvements for cell phones may simply result in greater phone usage. It is therefore unclear how much green and brown efficiency innovation has affected direct and indirect carbon emissions. These are the questions we explore in this section by exploring in turn the effects of innovation on: i) the companies' own future direct and indirect emissions; ii) the effects on other companies' direct and indirect emissions in the same industry; iii) the effects on carbon emissions across other, broadly related industries; and iv) the effects on carbon emissions across countries within the same industry.

3.5.1 Green Innovation and the CO2 Problem

We begin our analysis of the impact of green R&D on carbon emissions by estimating the following regression model linking future firm-level corporate policy outcomes, such as future carbon emissions, to measures of contemporaneous green and brown

efficiency patent ratios. Our first model exploits both extensive and intensive margins of patenting. Formally, we estimate the following linear regression model:

$$CorporatePolicy_{i,t+h} = a + b * PatentRatio_{i,t} + c * Controls_{i,t} + FE + \epsilon_{i,t} \tag{3.2}$$

where *Corporate Policy* is a generic response variable that includes: i) the total level of emissions; ii) emission intensity; iii) INVEST/A; iv) LOGCAPEX; and v) LOGSALES, measured *t+h* years ahead. We let h take the value of respectively 1, 3, and 5 years to reflect the possibility that there may be a "time to build" lag in corporate adjustments. We also use the average value of patenting activity over the previous 3 years to predict corporate outcomes to take account of the fact that innovation breakthroughs are lumpy. The variable *Patent Ratio* is defined as before, and all regressions include year and firm-fixed effects. We double cluster standard errors at the firm and year dimensions. Our coefficient of primary interest is *b*, which measures the impact of *Patent Ratio* on future corporate policy outcomes.

The results are reported in Table 3.8. Panel A reports the effects of green innovation (GREENRATIOEP) on corporate policy outcomes one year (L1), three years (L3), and five years (L5) ahead. We also report the effects of green innovation averaged over the previous three years (3YEARAVGGREENRATIOEP) on these corporate policy outcomes. As shown in column 1, green innovation has no significant effects on firms' direct emissions, one, three, or five years later. The same is true for indirect emissions (scope 2 emissions in column 2, upstream scope 3 emissions in column 3, and downstream scope 3 emissions in column 4[13]), although we observe a small reduction in indirect emissions with a 10% statistically significant negative coefficient of -0.042 for scope 2 emissions three years after the green patent filings. Future emissions are also not significantly related to innovation activity averaged over the past three years. We conclude that green innovation has not resulted in significant carbon emission reductions for the innovating firms even after five years since the patent filing. Columns

[13]Note that since downstream scope 3 emissions data has become available only in recent years, we do not have sufficient data to explore the effects on downstream scope 3 emissions over a 5-year horizon.

4 to 8 further report the lack of any significant effects of green innovation on direct or indirect emission intensity, so that the green technical progress does not appear to have materialized in any significant carbon efficiency gains. The only significant effect of green innovation on future corporate policies has been on future investment (with a three-year lag), with a substantial reduction in investment following the green patent filings. This latter finding is somewhat surprising, given that one expects research breakthroughs to be followed by development (i.e., more investment).

Panel B reports the effects of brown efficiency innovation (BROWNEFFRATIOEP) on corporate policy outcomes again respectively one year (L1), three years (L3), and five years (L5) ahead. As before we also report the effects of brown efficiency innovation averaged over the previous three years (3YEARAVGBROWNEFFRATIOEP) on these corporate policy outcomes. We find few significant effects of innovation on future corporate policies, except for a small increase in direct emissions with a 10% statistically significant positive coefficient of 0.065 for scope 1 emissions five years after the brown efficiency patent filings (in column 1), and a stronger, positive effect of average brown innovation on scope 1 emissions. This finding suggests that far from reducing future emissions, brown efficiency innovations result in increased future emissions. However, we also find a small improvement in scope 2 emission intensity, with a 10% statistically significant negative coefficient of -0.019 for scope 2 emission intensity five years after the brown efficiency patent filings (in column 7). Yet, this latter effect must be set against the significant effects on other corporate policies such as an increase in sales (column 12). Overall, what emerges from these findings is a picture that is consistent with the Jevons paradox: although brown efficiency innovation produces carbon intensity efficiency gains (for scope 2 emissions), these gains are offset by operating expansions (sales), which on net result in higher scope 1 emissions.

For robustness, we consider several alternative specifications. First, in Table B.XIV we confirm the insignificance of firm-level green and brown innovation in affecting future carbon emissions and other corporate outcomes, for the specification where we include only observations of firms that hold at least one green, respectively brown,

patent (intensive margin). Second, in Table B.XV we show the results from the regressions where we take patent counts rather than patent ratios as the main independent variable. The main difference is that the average count of green patents *positively* predicts future scope 1, scope 2, and upstream scope 3 emissions (in Panel A). Another related effect is that the average count of green patents *positively* predicts future firm sales. In contrast, we find a strong negative relationship between brown patent counts and scope 2 emissions (in Panel B). We also find a decrease in upstream scope 3 intensities in some specifications. Third, we explore how the importance of the patent matters for future corporate outcomes. In Table B.XVI we consider the maximum number of cites a firm's patent receives. We find a strong positive effect of green patent cites on future scope 2 emissions, and a slightly weaker effect on upstream scope 3 emissions. In turn, green patent citations negatively predict downstream scope 3 emissions one year and three years into the future. Brown patent citations do not seem to affect future emissions, except for scope 1 emissions which fall in the next 1-3 years for companies with high citations of brown patents. In Table B.XVII we look at the number of blockbuster patents a firm generates. As before, we find that, if anything, a higher incidence of blockbuster green patents is associated with higher levels of total emissions and particularly upstream scope 3 emissions. All other emissions components are unrelated to this measure. We also find little evidence that blockbuster brown patents lead to any reduction in future emissions. In Table B.XVIII we restrict our analysis to companies whose cumulative patent ratio falls in the top quintile of the empirical distribution based on the previous 5-year data. Among all these innovation metrics, we find that the only model that predicts a reduction in future emissions is the 3-year moving average measure of green patents, which is negatively associated with scope 2 emissions. For brown patents, we find instead that the moving average of brown innovation strongly predicts a future increase in scope 1 emissions. Finally, in Table B.XIX we show the results from using alternative, OECD-based, patent classifications. For green patents, we find some evidence of a reduction in future scope 2 emissions based on the ratio of green patents. Still, total future emissions are not negatively as-

sociated with this predictor. We also find a reduction in scope 2 emissions for some specifications based on brown patents, but the overall evidence of a link between green innovation and future decarbonization is weak. The conclusion we draw is that companies' green R&D activities are largely divorced from their other operations. Based on this evidence we conclude that the *green industrial* revolution has not yet materialized and that green innovation *per se* as the solution to the energy transition and the path to net-zero is still more of a promise than a reality.

If green or brown innovation does not lead to future carbon emission reductions by the innovating firms, could it be that these innovations are adopted by other firms so that green innovation activity *spills over* to the industry as a whole and materializes in industry-wide emission reductions? We explore this question by linking industry-level direct and indirect carbon emissions, carbon intensity, and investment, to respectively green and brown efficiency innovation activity in the industry. Our baseline specification uses the GICS-6 industries classification. All regressions include the same controls as before, except that they are now measured at the industry level. We also include year and industry fixed effects. We double cluster standard errors at the industry and year levels. We report our findings for the industry-wide effects of green innovation in Table 3.9, Panel A, and of brown innovation in Table 3.9, Panel B.

Consider first the effects of green innovation. In Panel A.1 we consider the effects on all firms within the same industry, whether they are innovators themselves or not. We find that green innovation is positively associated with future scope 1 emissions in the same industry, especially in the longer 5-year horizon. This result is largely driven by an increase in industry sales, in line with Jevons' paradox. In fact, we find that scope 1 emission-intensity at the industry level goes down. We further find that a greater rate of green innovation in the industry is associated with higher future scope 2 emissions, consistent with the displacement effect. Finally, we find that more green innovation is associated with significant upstream carbon emission-intensity improvements.[14] One consistent interpretation of these latter findings could be that reduced

[14]Table B.XX considers green citations. While the results on absolute scope 1 emissions, intensities and

upstream scope 3 intensity is achieved by switching energy sources towards electricity, and the increase in electricity usage may have been met by electricity produced by fossil-fuel based power plants, which would increase scope 2 intensity. We note that the above results do not change much if we take as our measure of green innovation the average of green patenting activity over three years (3YEARAVGGREENRATIO) to take account of the fact that innovation is a gradual multi-year process. Finally, we also find a small significant effect on industry-wide investment, with greater green innovation associated with a subsequent slight increase in investment, especially in the longer run.

We also break down within industry spillover effects by looking separately at firms that innovate and those that do not. The reason why we make this distinction is that spillovers among innovating firms could be driven by competition, whereas spillovers from innovating firms to non-innovating firms are driven by adoption of the new green technologies. In Panel A.2 of Table 3.9 we report the results of the effects of green innovation on corporate policies of all the innovating firms in the industry. Again, we find no effect of green innovation on subsequent carbon emission reductions even though the direction of the effect for scope 1 emissions becomes negative, suggesting a more beneficial effect of green innovation. Still, we find that greater green innovation is associated with higher scope 2 emissions, especially over the longer 3-year period. In Panel A.3 we report the results of the effects of green innovation on corporate policies of all the non-innovating firms in the industry. We find no evidence of any within-industry *spillover* between green innovators and non-innovators.[15] There is no significant subsequent carbon emission reduction by the non-innovators in the industry. There is, however, a significant increase in scope 2 carbon emission levels and intensity for the non-innovating firms. We also find a positive effect for scope 1 emissions.

sales have the same sign, they are statistically weaker. Table B.XXI looks at OECD green patent ratios. The results reported in this table broadly confirm our findings. Scope 3 upstream intensities again improve with more green innovation. Note that we also find small reductions in scope 1 emissions for a 3-year lag for ever patenting firms, but this effect disappears for a 5-year lag.

[15] In Table B.XX these results are confirmed with patent citations as a measure of green innovation, except for an increase in scope 3 downstream emissions with a 3 year lag.

In our tests, we assume a particular granularity in which innovation propagates within industries. The choice of a proper sectoral clustering is ex ante difficult even though GICS-6 is the preferred classification of investors. As a robustness, we therefore repeat the same analysis in Panel A of Table B.XXII, but with a different industry classification: Instead of the coarser GICS-6 classification we use the slightly finer Trucost industry classification. Most of the qualitative results are similar, with some notable exceptions. We now find that most of the industry-level emission metrics are unrelated to industry-level green ratios. The exceptions are for scope 2 intensity and scope 3 downstream emissions, both being positively related to green innovation. In sum, what emerges from these findings is that there is no evidence of significant industry-wide direct and indirect emission reductions following greater green patenting activity and if anything, some of the emissions, especially scope 2 emissions go up, consistent with the displacement effect.

We consider next the industry-wide effects of brown efficiency innovation. The results are reported in Panel B of Table 3.9. In Panel B.1 we again look at the effects on all firms in the industry, whether they are innovators themselves or not. Interestingly, we find some reduction in direct or indirect carbon emissions following greater brown patenting activity even though the results are statistically insignificant.[16] We further find that scope 1 and scope 3 upstream carbon emission-intensity goes up. Another remarkable finding is the apparent heterogeneity between innovating and non-innovating firms. While emissions of innovating companies in the same GICS-6 industry increase slightly, carbon emissions of the non-innovating firms in the sector (both direct and indirect) go down. Interestingly, this effect is to a large extent driven by a reduction in sales, and investments, of that group of companies. Hence, the carbon emissions reduction of this subset of companies is largely coming from their loss of market share and not from a greater carbon efficiency of production. We again repeat the same analysis in Panel B of Table B.XXII with the Trucost industry classi-

[16] In Table B.XX we explore the robustness of these findings to using patent citations to measure brown innovation. Under this measure the results are broadly confirmed, although absolute scope 1 emission and intensities increase in the long-run.

fication. Most of the qualitative results are similar, even though we find that scope 2 emissions of innovating companies go down due to increased efficiency of energy production. At the same time, we again find that the market share of non-innovating companies goes down by a significant margin thus explaining some of the reduction in total emissions.

If there are no significant effects of green innovation on industry-wide carbon emissions, could there be cross-industry effects? Could it be that technological improvements in green energy in one industry mainly result in carbon emission reductions in other, closely related industries? We explore this question next (we also look at cross-country spillovers within individual sectors in Tables B.XXIII-B.XXVII of the Appendix). In Table 3.10 we associate industry-wide direct and indirect carbon emissions, scope 1, 2, and 3 carbon intensity, capital expenditures, and sales in a given industry with green innovation activity by firms outside the narrow sector, but within the broader sector, and ask to what extent green innovation works by reducing emissions across sectors. Specifically, we link innovation activity in a given GICS-8 industry to corporate outcomes in a corresponding GICS-2 industry, excluding the specific GICS-8. In Panel A.1 we include all firms, in Panel A.2 we only look at cross-sector spillovers on innovating firms and in Panel A.3 we only look at cross-sector spillovers on non-innovating firms. Interestingly, we find a significant cross-industry spillover effect on carbon emissions with a 1-year lag for upstream scope 3 emissions, and for downstream scope 3 emissions for green innovation activity averaged over three years (3YEARAVGGREENRATIOEP). This effect works entirely through innovating firms, as is shown in Panels A.2 and A.3.

As for the cross-industry effects of brown efficiency innovation reported in Panel B of Table 3.10, we find that the only significant cross-industry effect on the level of emissions is an increase in downstream scope 3 emissions. The other cross-industry effect is a significant worsening of scope 1 and scope 2 carbon intensity for patenting firms. These findings point to other channels through which rebound effects can take place. An efficiency gain in brown technology in one sector can result in increased

carbon emissions in another sector (through the supply chain) by inducing greater use of a complementary brown technology.

These findings are consistent with the general idea that cross-sector innovation is highly complementary, and that it takes innovation breakthroughs in multiple sectors to be able to implement new technologies that reduce carbon emissions at scale. Moreover, technological innovation in one sector can result in rebound effects in another sector, largely eliminating any reductions in direct emissions from the innovation. This points to the complexity of green innovation as a solution to the CO2 problem. Decentralized, market-based, innovation may not be all that effective in decarbonizing the economy, if adoption and scaling of green technologies is held back by the lack of coordination of innovation across firms and sectors.

3.5.2 Spillovers from the universe of privately held companies

Our results so far relate firm-level and industry-level emissions to innovation of publicly listed companies. Our focus on publicly listed firms is dictated by the availability of carbon emissions data for these companies. However, one could argue that such firms may benefit from innovation not only of similar publicly listed companies but also from innovation of privately held firms. In this section, we examine this spillover channel by looking at industry-level responses to green and brown innovation by publicly listed and privately held companies, separately.

In Table 3.11, we report the results from the analysis that considers innovation and output in the same GICS-6 industry, similar to our setting in Table 3.9. In Panel A, we look at the role of green innovation. We define two new variables: GREENRATIOEP PUBLIC takes innovation activity of all publicly listed companies, GREENRATIOEP PRIVATE uses the innovation of private companies. Both measures incorporate scaling by total innovation activity. In Panel A.1, we focus on all firms with emissions data. We find that neither public nor private innovation is associated with any statistically significant reduction in industry-level emissions. Notably, we find that green

innovation in the public sector is more positively correlated with future scope 2 emissions, as well as scope 1 and upstream scope 3 emissions, though the effects for the latter two are statistically insignificant. The stronger positive association of public innovation mostly comes from the subset of innovating companies (as reported in Panel A.2), which are also the ones whose sales go up by more.

In Table 3.11, Panel B, we repeat the same analysis for brown innovation. The corresponding new variables of interest are BROWNEFFRATIOEP PUBLIC and BROWNEFFRATIOEP PRIVATE. In contrast to the results in Panel A, we find that public and private innovation do not seem to have markedly different impacts on future industry-level emissions. This result is consistent with the common perception that private firms are more involved in green innovation.

In Table 3.12, we provide additional evidence on the role of public and private innovation through the lens of cross-industry spillovers. Here, our research design follows that in Table 3.10. In Panel A, we consider green innovation. Several interesting findings emerge. First, in aggregate, private innovation seems to have a large impact on industry-level emission reductions in the public sector. This result largely comes through the reduction of scope 3 emissions, both upstream and downstream. Second, this effect is mostly driven by the fact that an increase in private green innovation predicts a reduction in sales of public firms. It seems that innovating private firms are encroaching on the market position of public firms. Third, the effect on upstream scope 3 emission reductions is mostly due to the impact on innovating firms, while downstream scope 3 emission reductions are more associated with green innovation in public firms. In Panel B, we report corresponding results for brown innovation. We find some evidence that brown innovation, both in the public and private firms, reduces scope 1 emissions, although the results are generally statistically weak. The only notable exception is the positive effect of innovation of public firms on the reduction in scope 1 emissions of innovating firms. In turn, innovation among public firms positively predicts scope 2 emissions, especially those of innovating firms.

Another channel through which the Jevons paradox can manifest itself is through product market competition. Our measure of competition is the company's market share (in terms of sales) relative to the total sales of both public and private firms within the same GICS-6 industry. As we show in Table 3.13, green innovation and the adoption of green technologies can be a handicap in product market competition if green firms have higher production costs than brown firms. In Panel A, we estimate a model with industry*year fixed effects and in Panel B a model with firm fixed effects. As is shown in columns 1 to 3, a firm's market share is significantly negatively impacted by past green innovation activity, whether on a 1-year, 3-year, or 5-year lag. This effect is largely due to cross-firm variation, given that the effects become weaker when we account for firm-fixed effects. In contrast, there is no significant effect of brown efficiency innovation activity on firms' market share. If anything, the effect of brown efficiency innovation is to increase market share. Thus, even if green innovation could reduce future carbon emissions of green firms, this positive effect is partially undone by the increased market share of brown firms.

3.5.3 The relative importance of green innovation for decarbonization

Having highlighted the tenuous association between green (or brown) innovation and future carbon emission reductions, we explore next the extent to which corporate carbon emissions are explained by green innovation. In the first test, reported in Table 3.14, we conduct a balance test by comparing two samples of firms: those with decreasing emissions and those with increasing emissions. We perform this comparison for scope 1 emission in Panel A and the total level of direct and indirect emissions in Panel E. In Table B.XXIX, we also consider scope 2, scope 3 upstream and scope 3 downstream. In the group of firms that decrease (increase) their emissions over time we further divide firms into the 50% of companies with the largest emission reductions (surges). For each group, we report the means and standard deviations of

different characteristics and the test of differences in means between each pair.

In Panel A, we show the results based on scope 1 emissions. We find that companies with extreme increases and decreases in emissions are not very different from each other in terms of their green patent ratios as well as their brown efficiency patent ratios. The two types of companies have also very similar levels of patent citations. On the other hand, firms that decrease their scope 1 emissions are on average larger and older than companies that increase their emissions; they also have lower M/B ratios, and negative sales growth. However, they are not very different in their ROE or leverage metrics. The similarities in innovation ratios are also observed when we consider the sum of scope 1, scope 2, and scope 3 emissions in Panel B.

In Table B.XXIX Panel A, we report the results for scope 2 emissions. Results are qualitatively similar to those for scope 1 emissions, except that now emission reducing companies on average have higher brown efficiency patent ratios. They are also less profitable and have lower leverage ratios. In Table B.XXIX Panel B we look at the differences for upstream scope 3 emissions. For these indirect emissions, we find that emission reducing companies have higher green and brown efficiency patent ratios. These differences, however, disappear when we look at sorts based on downstream scope 3 emissions, as shown in Table B.XXIX Panel C. Overall, we conclude that companies that reduce their emissions the most are not necessarily more innovative than those that increase their emissions the least. We find that the two sets of companies significantly differ in their sales performance (changes in sales are negative on average for companies reducing emissions and positive for companies increasing emissions across all scopes) pointing again to the limited decoupling of growth and emissions.

In another set of tests, we study the economic significance of green innovation using the two following specifications. First, we look at the relationship between the stock of innovation and subsequent long-term changes in emissions. This test allows us to account for the fact that innovation can be a process with a long gestation period. Specifically, we predict the firm-level absolute change in average emission levels and their

intensities between the periods 2005-2014 and 2015-2020 using measures of the stock of innovations (measured either as patent ratios or as patent counts) over two time periods: (i) 1990-2004; and (ii) 1990-2014. We perform the tests separately for green and brown innovation. We show the results of this test in Table 3.15. Panel A presents the results based on patent ratios. We find that the long-term stock of green or brown innovation measured by patent ratio is not related to long-term changes in emissions. Whether we use the shorter or the longer period to cumulate innovation, the results are not statistically significant. If anything, the correlations between the stock of green innovation and future emission changes is positive, which suggests that companies with greater patenting activity on average increased their emissions. In contrast, we find some albeit weak evidence that over a more prolonged period, companies with higher brown efficiency patents reduced their emissions. The results become slightly stronger when we look at the cumulative number of patents, as presented in Panel B. Now the number of green patents accumulated over a longish period predicts subsequent reductions in future scope 1 and scope 3 upstream emissions. The result is statistically weaker when we look at brown innovation. Overall, even though we find some evidence that over the long-run innovation may lead, in some cases, to reductions in emissions this result may not necessarily offer a silver bullet from the perspective of supporting current innovations, simply because we do not have that much time to wait for the emissions reductions from innovation to materialize.

Another question of interest is whether the effect of green innovation is economically large. This is the question we try to answer in Table 3.16. Here we evaluate the partial R2 of the regression model that tries to explain future emissions levels using patent ratios. As before, we focus on green and brown efficiency patents, and consider various predictive horizons. The consistent message that emerges from this analysis is that green innovation activity explains a very small fraction of the variation in future emissions levels. The partial R2s typically do not exceed 1% and more frequently are significantly smaller. We conclude that green innovation is not a primary source of firm-level variation in future carbon emissions. Even if some companies do decar-

bonize their operations, this decarbonization is explained only to a very limited extent by these firms' green patenting activity.

3.6 Conclusion

What emerges from our analysis of green innovation is that the predicted sustainability revolution has not yet begun. Although there has been a steady increase in green and brown efficiency innovation, these technological advances have not materialized in lower carbon emissions. Most of the green innovation is done by firms that are already green (with low carbon emissions) but brown companies (with high carbon emissions) tend to engage in brown efficiency innovation. Much of the promise of the latter technological advances in terms of lower carbon intensity has been undone by rebound effects. Furthermore, where we see significant decarbonization, it has little to do with green technological advances.

We cannot determine what the counterfactual would be, had there been much less green innovation. It is possible that in the absence of all this innovation activity, carbon emissions might have been much higher. Also, as the IEA (2020) report contends, the path to decarbonization "will require a broad range of different technologies working across all sectors of the economy in various combinations and applications." What we have found, however, is that green innovation has not yet put the economy on a net zero compatible trajectory. Green innovation may be necessary, but it is not sufficient on its own to bring about a renewable energy transition.

A major obstacle to green innovation is Arrow's (1962) replacement effect. Fossil fuel-based profitable businesses have little incentive to engage in green innovation that might undermine their business model. But we have found a much more pervasive replacement effect at work, through companies' supply chains and ecosystems. When upstream suppliers and downstream clients have fossil-fuel based operations it is very difficult and costly for individual companies to switch to a green technology. Hence,

their lack of interest in green innovation. Not a day goes by without some major announcement of a promising technological breakthrough that might solve the CO2 problem, whether it is molten-salt nuclear reactors, power-to-gas (P2G) renewable hydrogen production, nuclear fusion, modular carbon capture systems, or sodium-sulphur batteries, etc. Yet, as promising as these technological breakthroughs sound, what ultimately matters for the transition to net zero is adoption of these green technologies at scale. And for this to happen in an accelerated way to avoid further overheating of the planet, what may be required is public policy intervention to coordinate adoption. This calls for a new form of industrial policy that breaks through the replacement obstacle by coordinating green technology adoption upstream and downstream throughout firms' ecosystems. Moreover, subsidies for green innovation must be more carefully targeted to where they help unlock a general adoption of green technologies throughout the supply chain. Blanket subsidies for innovation without regard to the likely adoption of new technologies may simply be too wasteful and costly.

3.7 Tables

Table 3.1. Capacity constraints

The unit of observation is firm-year. The sample period is 2005-2020. In Panel A, the dependent variable is ANYCOUNTEP in columns 1 to 3 and ANYCOUNTEP w/o zeros in columns 4 to 6. ANYCOUNTEP is the number of granted or purchased patents by the European Patent Office (EP) per firm and year. In Panel B the dependent variable is GREENCOUNTEP in columns 1 to 3 and BROWNEFFCOUNTEP in columns 4 to 6. GREENCOUNTEP is the number of granted or purchased "green" patents by the EP per firm and year, while BROWNEFFCOUNTEP covers "brown efficiency" patents. The independent variables are defined as follows: *Age* is the firm age based on its year of incorporation; *PATSTOCKANYEP* (*PATSTOCKGREENEP* and *PATSTOCKBROWNEFFEP*) is the firm's patent stock of all (green and brown efficiency) granted or purchased patents by the EPO from 1990 up to year t; *LOGASSETS* is the natural logarithm of total assets (in $ million); *LOGSIZE* is the natural logarithm of market capitalization (in $ million); *LOGNOEMPL* is the natural logarithm of the number of employees; *LOGPPE* is the natural logarithm of plant, property & equipment (in $ million); *LEVERAGE* is the book value of leverage defined as the book value of debt divided by the book value of assets; *ROE* is the return on equity; M/B is the market value of equity divided by the book value of equity; $INVEST/A$ is CAPEX divided by the book value of assets; *BETA* is the firm-level market beta estimated over the one-year period; *VOLAT* is the monthly stock return volatility calculated over the one year period; *MOM* is the cumulative stock return over the one-year period; *RET* is the monthly stock return in December; *MSCI* is an indicator variable equal to one if a stock is part of the MSCI ACWI in a given year and zero otherwise. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any innovation						
	ANYCOUNTEP w. zeros			*ANYCOUNTEP* w/o zeros		
PATSTOCKANYEP (/100)	0.017***	0.012***	−0.002***	0.016***	0.013***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LOGASSETS	−0.121***	0.465***	0.192***	0.058**	0.411***	0.178***
	(0.019)	(0.054)	(0.057)	(0.023)	(0.048)	(0.057)
LOGNOEMPL	0.333***	0.127***	0.049**	0.284***	0.132***	0.050**
	(0.015)	(0.020)	(0.024)	(0.017)	(0.018)	(0.024)
AGE (/100)	0.153***	0.115***		0.073**	0.096***	
	(0.032)	(0.026)		(0.030)	(0.025)	
LOGSIZE	0.620***	0.266***	0.028	0.408***	0.238***	0.032
	(0.024)	(0.029)	(0.023)	(0.024)	(0.024)	(0.023)
LOGPPE	−0.026**	0.004	0.114**	−0.116***	−0.038	0.112**
	(0.013)	(0.035)	(0.045)	(0.019)	(0.037)	(0.045)
LEVERAGE	−0.010***	−0.004***	−0.003***	−0.008***	−0.003***	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROE	−0.210**	−0.036	−0.086**	−0.123*	−0.011	−0.089**
	(0.087)	(0.069)	(0.041)	(0.070)	(0.057)	(0.041)
M/B	−0.028***	0.007	0.001	−0.015**	−0.001	0.001
	(0.008)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)
INVEST/A	−0.017***	−0.000	−0.001	0.003	0.007	−0.001
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
BETA	0.330***	0.122***	0.029	0.262***	0.153***	0.033
	(0.037)	(0.034)	(0.022)	(0.035)	(0.032)	(0.022)
VOLAT	2.890***	1.458***	−0.313	2.223***	1.123***	−0.265
	(0.251)	(0.273)	(0.242)	(0.327)	(0.328)	(0.244)
MOM	−2.715***	−0.949*	0.199	−2.334***	−0.988*	0.182
	(0.623)	(0.555)	(0.300)	(0.580)	(0.513)	(0.301)
RET	0.000	0.070	−0.009	−0.006	0.035	−0.002
	(0.181)	(0.138)	(0.074)	(0.163)	(0.130)	(0.075)
MSCI	0.025	0.028	0.055*	−0.014	0.013	0.044
	(0.044)	(0.032)	(0.029)	(0.040)	(0.029)	(0.029)
Constant	−4.678***	−4.577***	1.497***	−2.763***	−3.365***	1.621***
	(0.137)	(0.143)	(0.318)	(0.136)	(0.142)	(0.321)
Observations	68496	63945	37250	24960	23699	23828
Pseduo R2	0.654	0.835	0.921	0.642	0.809	0.910
Panel B: Green or brown efficiency innovation						
	GREENCOUNTEP			*BROWNEFFCOUNTEP*		
PATSTOCKGREENEP (/100)	0.121***	0.139***	0.013***	−0.175***	−0.045***	−0.073***
	(0.007)	(0.009)	(0.004)	(0.018)	(0.011)	(0.011)
PATSTOCKBROWNEFFEP (/100)	−0.037***	−0.086***	−0.022***	0.305***	0.135***	0.060***
	(0.012)	(0.010)	(0.008)	(0.017)	(0.012)	(0.015)
AGE (/100)	0.238***	0.041		0.636***	0.342***	
	(0.044)	(0.039)		(0.053)	(0.065)	
LOGSIZE	0.348***	0.362***	0.147***	0.321***	0.380***	0.193***
	(0.027)	(0.037)	(0.029)	(0.047)	(0.062)	(0.049)
LOGPPE	0.190***	0.332***	0.093***	0.272***	0.354***	−0.069
	(0.023)	(0.040)	(0.035)	(0.039)	(0.077)	(0.048)
LEVERAGE	−0.009***	−0.004***	−0.006***	−0.002	0.004	0.016***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)
ROE	−0.246**	−0.179**	−0.134**	0.091	0.156	−0.232**
	(0.111)	(0.072)	(0.065)	(0.307)	(0.208)	(0.114)
M/B	−0.017	−0.015	−0.016**	−0.058***	−0.054***	−0.021*
	(0.011)	(0.010)	(0.007)	(0.021)	(0.018)	(0.012)
INVEST/A	0.000	−0.020***	−0.005	−0.003	−0.023***	0.012
	(0.007)	(0.005)	(0.005)	(0.009)	(0.008)	(0.010)
BETA	0.607***	0.226***	0.005	0.567***	0.185***	−0.051
	(0.051)	(0.045)	(0.031)	(0.084)	(0.071)	(0.060)
VOLAT	2.950***	2.769***	−0.252	1.624**	0.732	−0.572
	(0.461)	(0.340)	(0.347)	(0.728)	(0.705)	(0.610)
MOM	−1.522*	−1.751**	−0.923**	−0.087	−1.994	0.442
	(0.814)	(0.716)	(0.388)	(1.357)	(1.244)	(0.672)
RET	0.201	0.207	0.275**	−0.817**	0.080	−0.306
	(0.237)	(0.226)	(0.117)	(0.379)	(0.326)	(0.234)
MSCI	0.234***	0.128***	0.005	0.044	0.184**	0.094
	(0.053)	(0.047)	(0.049)	(0.101)	(0.077)	(0.061)
Constant	−3.770***	−4.186***	1.389***	−5.260***	−5.087***	1.552***
	(0.170)	(0.144)	(0.371)	(0.262)	(0.282)	(0.487)
Observations	27860	24818	20173	27767	20143	12186
Pseudo R2	0.561	0.730	0.832	0.529	0.755	0.825
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes

Table 3.2. Patent Ratios and Firm Type

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOEP* in columns 1 to 3 and *BROWNEFFRATIOEP* in columns 4 to 6. *GREENRATIOEP* is the number of green patents over the total number of patents granted or purchased at the firm and year level based on European Patent Office patents. *BROWNEFFRATIOEP* similarly is the number of brown efficiency patents over the total number of patents at the European Patent Office. *LOGS1TOT* is the natural logarithm of firm-level scope 1 emissions. All other variables are defined in Table 3.1. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOEP			*BROWNEFFRATIOEP*		
LOGS1TOT	0.091***	−0.053***	0.013	0.058***	0.049**	−0.064**
	(0.008)	(0.011)	(0.015)	(0.014)	(0.020)	(0.032)
AGE (/100)	−0.303***	−0.186***		0.235***	0.213***	
	(0.033)	(0.030)		(0.045)	(0.050)	
PATSTOCKGREENEP (/100)	0.052***	0.035***	−0.002			
	(0.004)	(0.004)	(0.003)			
PATSTOCKBROWNEFFEP (/100)				0.099***	0.047***	−0.001
				(0.009)	(0.008)	(0.008)
LOGSIZE	−0.192***	−0.111***	0.048**	−0.303***	−0.083***	−0.071
	(0.016)	(0.018)	(0.022)	(0.032)	(0.031)	(0.045)
LOGPPE	0.124***	0.137***	−0.042*	0.277***	0.039	−0.017
	(0.016)	(0.018)	(0.023)	(0.033)	(0.031)	(0.052)
LEVERAGE	−0.006***	−0.004***	0.001	−0.005***	−0.001	−0.005*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
ROE	−0.312***	−0.123**	−0.014	0.406***	0.117	−0.048
	(0.054)	(0.050)	(0.033)	(0.090)	(0.087)	(0.086)
M/B	0.020***	0.020***	−0.004	−0.022**	−0.011	0.004
	(0.006)	(0.006)	(0.005)	(0.011)	(0.011)	(0.014)
INVEST/A	0.010***	0.008**	0.005*	0.001	0.004	0.006
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.008)
BETA	0.210***	0.100***	−0.017	0.311***	−0.018	0.034
	(0.035)	(0.037)	(0.027)	(0.062)	(0.058)	(0.047)
VOLAT	1.956***	1.333***	−0.004	0.210	0.154	0.392
	(0.221)	(0.232)	(0.178)	(0.469)	(0.523)	(0.493)
MOM	0.402	−0.011	0.049	1.508*	0.786	0.546
	(0.456)	(0.453)	(0.289)	(0.898)	(0.850)	(0.657)
RET	−0.132	−0.249**	0.041	−0.357	−0.003	−0.167
	(0.121)	(0.116)	(0.073)	(0.232)	(0.236)	(0.179)
MSCI	0.070**	0.042	0.048	0.028	0.124**	−0.080
	(0.032)	(0.031)	(0.035)	(0.057)	(0.053)	(0.064)
Constant	2.482***	3.205***	3.081***	1.287***	2.339***	4.217***
	(0.094)	(0.096)	(0.199)	(0.170)	(0.184)	(0.458)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	27860	24818	20173	27767	20143	12186
Pseudo R2	0.0775	0.317	0.516	0.0989	0.439	0.527

Table 3.3. Patent Ratios and Firm Type - Intensive Margin

The unit of observation is firm-year. The sample period is 2005-2020 and the sample restricts inclusion to firm-years with *at least one* green patent at the European Patent Office in columns 1 to 3 and one brown efficiency patent at the European Patent Office in columns 4 to 6. The dependent variable is *GREENRATIOEP* in columns 1 to 3 and *BROWNEFFRATIOEP* in columns 4 to 6. All variables are defined in Table 3.1, Table 3.2 and Table 3.2. All independent variables are lagged by one year. The model is estimated using a pooled regression model. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOEP			*BROWNEFFRATIOEP*		
LOGS1TOT	1.571***	−1.587***	−0.291	0.376*	−0.400	−0.253
	(0.170)	(0.252)	(0.273)	(0.197)	(0.340)	(0.506)
AGE (/100)	−6.809***	−3.153***		−0.989	−0.406	
	(0.601)	(0.603)		(0.649)	(0.803)	
PATSTOCKGREENEP (/100)	0.756***	1.024***	0.477***			
	(0.091)	(0.103)	(0.072)			
PATSTOCKBROWNEFFEP (/100)				1.360***	1.101***	0.266*
				(0.140)	(0.176)	(0.140)
LOGSIZE	−6.749***	−5.387***	0.601	−5.912***	−4.414***	−0.884
	(0.348)	(0.425)	(0.399)	(0.415)	(0.574)	(0.724)
LOGPPE	0.657*	0.178	−1.067**	0.011	−2.183***	−0.977
	(0.342)	(0.396)	(0.450)	(0.382)	(0.469)	(0.769)
LEVERAGE	−0.071***	−0.117***	0.027	−0.006	−0.124***	−0.016
	(0.020)	(0.021)	(0.020)	(0.027)	(0.033)	(0.041)
ROE	−6.178***	−2.141*	0.636	0.388	1.427	−0.809
	(1.269)	(1.276)	(0.736)	(1.804)	(2.027)	(1.307)
M/B	0.530***	0.517***	−0.017	0.169	0.063	0.127
	(0.128)	(0.131)	(0.091)	(0.186)	(0.211)	(0.185)
INVEST/A	0.375***	0.314***	0.088	0.493***	0.250*	0.046
	(0.088)	(0.095)	(0.085)	(0.126)	(0.151)	(0.123)
BETA	1.175	1.230	−0.667	0.266	0.051	−0.185
	(0.724)	(0.827)	(0.480)	(0.898)	(1.121)	(0.681)
VOLAT	37.812***	32.622***	6.636	−3.494	−13.215	−2.030
	(7.437)	(8.186)	(4.126)	(10.481)	(12.975)	(6.867)
MOM	15.039	0.793	−5.105	5.322	15.162	16.336*
	(11.472)	(12.330)	(6.025)	(15.864)	(19.737)	(9.515)
RET	−2.251	−3.345	−0.178	−4.578	1.966	−4.710*
	(3.029)	(3.253)	(1.620)	(3.993)	(4.982)	(2.474)
MSCI	−0.925	−0.650	−1.292**	−0.937	1.520	−1.771*
	(0.665)	(0.693)	(0.594)	(0.839)	(0.975)	(0.925)
Constant	69.208***	83.076***	30.172***	67.068***	80.924***	37.162***
	(2.276)	(2.655)	(3.701)	(2.984)	(4.158)	(6.783)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	no	yes	no	no	yes	no
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	12187	10957	11352	5550	4550	5114
R2	0.220	0.534	0.815	0.187	0.526	0.762

Table 3.4. Patent Citations and Firm Type

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENCITMAXEP* in columns 1 to 3 and *BROWNEFFCITMAXEP* in columns 4 to 6 in Panel A. In Panel B the dependent variable is *GREENBBCOUNTEP* in columns 1 to 3 and *BROWNEFFBBCOUNTEP* in columns 4 to 6. *GREENCITMAXEP* (*BROWNEFFCITMAXEP*) is the maximum number of forward citations any green (brown efficiency) patent of a firm received in a given year. *GREENBBCOUNTEP* (*BROWNEFFBBCOUNTEP*) is the number of green (brown efficiency) blockbuster patents patent per firm, where blockbuster patents are defined as patents in the 95th percentile based on the number of forward citations in a given grant year and classification. The regressions also include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables are lagged by one year and are defined in Table 3.1 and Table 3.2. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Maximum patent citation						
	GREENCITMAXEP			*BROWNEFFCITMAXEP*		
LOGS1TOT	−0.099***	−0.228***	−0.051	−0.032	0.079**	0.171*
	(0.024)	(0.057)	(0.066)	(0.028)	(0.036)	(0.089)
AGE (/100)	0.352**	0.711***		0.223*	−0.052	
	(0.172)	(0.175)		(0.115)	(0.089)	
PATSTOCKGREENEP (/100)	0.061***	0.067***	−0.017			
	(0.009)	(0.009)	(0.014)			
PATSTOCKBROWNEFFEP (/100)				0.093***	0.081***	0.034**
				(0.009)	(0.011)	(0.015)
Observations	21012	18737	15133	16885	12508	7430
Pseudo R2	0.400	0.658	0.725	0.415	0.719	0.701
Panel B: Blockbuster counts						
	GREENBBCOUNTEP			*BROWNEFFBBCOUNTEP*		
LOGS1TOT	−0.034**	−0.015	−0.016	0.081***	0.096**	−0.027
	(0.014)	(0.030)	(0.033)	(0.018)	(0.042)	(0.054)
AGE (/100)	0.052	0.044		0.555***	0.207***	
	(0.068)	(0.073)		(0.059)	(0.076)	
PATSTOCKGREENEP (/100)	0.099***	0.076***	−0.010			
	(0.006)	(0.006)	(0.007)			
PATSTOCKBROWNEFFEP (/100)				0.145***	0.119***	0.030
				(0.011)	(0.012)	(0.020)
Observations	27707	17910	10607	27178	9943	5439
Pseudo R2	0.314	0.444	0.459	0.348	0.564	0.517
Controls.	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes

Table 3.5. Patent Ratios and Firm Type: Market Share Interactions

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. MKTSHR TRUIND is a firm's market share based on its sales relative to total public and private firms' sales in a given Trucost sector. We report the coefficient on MKTSHR TRUIND as well as LOGS1TOT, AGE, PATSTOCKGREENEP (PATSTOCKBROWNEFFEP) and their interactions with MKTSHR TRUIND. The regressions also include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables are lagged by one year. The variables are defined in Table 3.1 and Table 3.2. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOEP			BROWNEFFRATIOEP		
LOGS1TOT	0.090***	−0.058***	0.009	0.085***	0.058***	−0.064*
	(0.008)	(0.012)	(0.015)	(0.015)	(0.021)	(0.034)
AGE (/100)	−0.363***	−0.260***		0.216***	0.192***	
	(0.039)	(0.037)		(0.053)	(0.058)	
PATSTOCKGREENEP (/100)	0.061***	0.059***	−0.006			
	(0.008)	(0.006)	(0.004)			
PATSTOCKBROWNEFFEP (/100)				0.101***	0.058***	−0.015
				(0.013)	(0.012)	(0.009)
MKTSHR TRUIND	−1.372***	−2.142***	−0.473	2.325***	0.689	−0.153
	(0.344)	(0.427)	(0.356)	(0.415)	(0.602)	(0.423)
LOGS1TOT X MKTSHR TRUIND	0.048	0.155***	0.044	−0.323***	−0.115*	0.034
	(0.038)	(0.044)	(0.041)	(0.055)	(0.064)	(0.056)
AGE (/100) X MKTSHR	0.761***	1.085***		0.184	0.224	
TRUIND	(0.152)	(0.182)		(0.196)	(0.284)	
PATSTOCKGREENEP (/100) X	−0.079**	−0.186***	0.037***			
MKTSHR TRUIND	(0.032)	(0.028)	(0.014)			
PATSTOCKBROWNEFFEP X				−0.004	−0.068	0.094***
MKTSHR TRUIND				(0.042)	(0.069)	(0.029)
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	27856	24814	20190	27763	20140	12187
Pseudo R2	0.080	0.319	0.516	0.102	0.439	0.525

Table 3.6. Patent ratios and Alternative Emissions

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOEP* in Panel A and *BROWNEFFRATIOEP* in Panel B. *LOGS2TOT* (*LOGS3UPTOT* and *LOGS3DOWNTOT*) is the natural logarithm of firm-level scope 2 (upstream 3 and downstream 3) emissions; *S1INT* (*S2INT*, *S3UPINT* and *S3DOWNINT*) is the the firm-level scope 1 (2, upstream 3 and downstream 3) emission intensity defined as the level of emission divided by the firm sales. The regressions also include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables are lagged by one year. The other variables are defined in Table 3.1 and Table 3.2. The model is estimated using Poisson pseudo-maximum likelihood. All regression include country and Trucost industry-year fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Green innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GREENRATIOEP						
LOGS2TOT	−0.056***						
	(0.012)						
LOGS3UPTOT		−0.128***					
		(0.018)					
LOGS3DOWNTOT			−0.025**				
			(0.010)				
S1INT (/100)				0.018			
				(0.335)			
S2INT					0.021		
					(0.025)		
S3UPINT						−0.036*	
						(0.018)	
S3DOWNINT							0.005***
							(0.002)
AGE (/100)	−0.189***	−0.176***	−0.186***	−0.195***	−0.194***	−0.194***	−0.193***
	(0.031)	(0.031)	(0.059)	(0.031)	(0.031)	(0.031)	(0.059)
PATSTOCKGREENEP (/100)	0.036***	0.035***	0.031***	0.035***	0.035***	0.034***	0.031***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)
Controls	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes	yes
Observations	24818	24818	7681	24818	24818	24818	7681
Pseudo R2	0.317	0.319	0.269	0.316	0.316	0.316	0.270

Panel B: Brown efficiency innovation							
	BROWNEFFRATIOEP						
LOGS2TOT	−0.031						
	(0.023)						
LOGS3UPTOT		0.149***					
		(0.031)					
LOGS3DOWNTOT			0.005				
			(0.023)				
S1INT				0.017***			
				(0.006)			
S2INT					−0.130**		
					(0.053)		
S3UPINT						0.139***	
						(0.028)	
S3DOWNINT							0.001
							(0.003)
AGE (/100)	0.217***	0.204***	0.301***	0.215***	0.213***	0.215***	0.304***
	(0.050)	(0.050)	(0.098)	(0.050)	(0.050)	(0.050)	(0.098)
PATSTOCKBROWNEFFEP (/100)	0.048***	0.047***	0.058***	0.047***	0.047***	0.049***	0.058***
	(0.008)	(0.008)	(0.015)	(0.008)	(0.008)	(0.008)	(0.015)
Controls	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes	yes
Observations	20143	20143	6426	20143	20143	20143	6426
Pseudo R2	0.439	0.440	0.420	0.439	0.439	0.440	0.420

Table 3.7. Patent Ratios and Firm Type post 2015

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. Panel A covers the full sample and Panel B the legacy sample, which restricts inclusion of firms into those that Trucost covers in its database before 2016. POST2015 is a dummy that is equal to 1 for all years after 2015 and zero otherwise. We interact this variable with all control variables. We report the coefficients of the following interactions: LOGS1TOT X POST2015, AGE X POST2015, PATSTOCKGREENEP (PATSTOCKBROWNEFFEP) X POST2015 and the triple interaction LOGS1TOT X AGE X POST2015. The regressions also include the following controls and their POST2015 interaction: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables other than POST2015 are lagged by one year. The variables are defined in Table 3.1 and Table 3.2. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Full sample	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOEP			BROWNEFFRATIOEP		
LOGS1TOT	0.069***	−0.072***	0.020	0.116***	0.071**	−0.085
	(0.015)	(0.018)	(0.022)	(0.025)	(0.031)	(0.053)
AGE (/100)	−1.036***	−0.914***		0.775***	0.478**	
	(0.146)	(0.135)		(0.187)	(0.191)	
PATSTOCKGREENEP (/100)	0.087***	0.059***	0.008			
	(0.009)	(0.009)	(0.007)			
PATSTOCKBROWNEFFEP (/100)				0.136***	0.021*	0.008
				(0.017)	(0.012)	(0.013)
LOGS1TOT X POST2015	−0.062***	−0.028	−0.013	−0.030	−0.036	−0.003
	(0.021)	(0.025)	(0.013)	(0.036)	(0.045)	(0.023)
LOGS1TOT X Age (/100)	0.081***	0.082***	−0.005	−0.068***	−0.038*	0.033
	(0.016)	(0.014)	(0.036)	(0.021)	(0.021)	(0.067)
AGE (/100) X POST2015	0.012	0.218		0.014	−0.306	
	(0.204)	(0.189)		(0.288)	(0.297)	
LOGS1TOT X POST2015 X Age	0.023	−0.012	0.007	−0.006	0.053	0.014
(/100)	(0.023)	(0.021)	(0.005)	(0.034)	(0.035)	(0.009)
PATSTOCKGREENEP (/100) X	−0.049***	−0.037***	−0.010**			
POST2015	(0.009)	(0.010)	(0.005)			
PATSTOCKBROWNEFFEP X POST2015				−0.046**	0.036**	−0.004
				(0.019)	(0.015)	(0.010)
Observations	27860	24818	20072	27767	20143	12147
Pseudo R2	0.0836	0.321	0.516	0.108	0.443	0.529
Panel B: Legacy sample						
	GREENRATIOEP			BROWNEFFRATIOEP		
LOGS1TOT	0.069***	−0.074***	0.019	0.116***	0.064**	−0.078
	(0.015)	(0.018)	(0.024)	(0.025)	(0.031)	(0.055)
AGE (/100)	−1.061***	−0.945***		0.796***	0.508***	
	(0.147)	(0.136)		(0.188)	(0.194)	
PATSTOCKGREENEP (/100)	0.087***	0.058***	0.008			
	(0.009)	(0.009)	(0.007)			
PATSTOCKBROWNEFFEP (/100)				0.136***	0.022*	0.009
				(0.017)	(0.012)	(0.013)
LOGS1TOT X POST2015	−0.024	0.001	−0.011	−0.015	0.005	−0.002
	(0.023)	(0.026)	(0.013)	(0.039)	(0.046)	(0.023)
LOGS1TOT X Age (/100)	0.082***	0.084***	−0.002	−0.069***	−0.040*	0.023
	(0.016)	(0.014)	(0.038)	(0.021)	(0.022)	(0.069)
AGE (/100) X POST2015	0.343	0.422**		0.098	−0.157	
	(0.227)	(0.204)		(0.311)	(0.323)	
LOGS1TOT X POST2015 X Age	−0.019	−0.034	0.007	−0.006	0.048	0.015*
(/100)	(0.025)	(0.022)	(0.005)	(0.037)	(0.038)	(0.009)
PATSTOCKGREENEP (/100) X	−0.047***	−0.030***	−0.011**			
POST2015	(0.009)	(0.010)	(0.005)			
PATSTOCKBROWNEFFEP X POST2015				−0.034*	0.037**	−0.003
				(0.020)	(0.015)	(0.010)
Observations	22990	20155	18275	22922	16164	11551
Pseudo R2	0.100	0.364	0.509	0.108	0.454	0.524
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes

Table 3.8. Patent Ratios and Firm-Level Outcomes

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 year. In Panel B, the key independent variable similarly is *BROWNEFFRATIOEP*. Controls include: *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. All variables are defined in Table 3.1 and Table 3.2 and are similarly lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENRATIOEP	0.021	−0.019	0.007	−0.046	0.004	0.019	−0.006	−0.009	−0.018	−0.048	−0.011	0.003
	(0.026)	(0.025)	(0.015)	(0.077)	(0.015)	(0.070)	(0.010)	(0.018)	(0.389)	(0.100)	(0.014)	(0.012)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.917	0.980
L3 GREENRATIOEP	0.002	−0.042*	0.000	0.032	−0.002	0.048	−0.000	0.002	−0.000	−0.166**	−0.009	−0.004
	(0.026)	(0.025)	(0.014)	(0.118)	(0.014)	(0.070)	(0.010)	(0.016)	(0.396)	(0.078)	(0.013)	(0.011)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 GREENRATIOEP	0.015	−0.036	0.009		0.013	0.125*	0.004	0.018		−0.109	−0.015	−0.006
	(0.028)	(0.026)	(0.017)		(0.017)	(0.069)	(0.010)	(0.018)		(0.079)	(0.013)	(0.013)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.972	0.933	0.981		0.888	0.956	0.989
L1 3YEARAVGGREENRATIOEP	0.007	−0.039	0.005	−0.157	−0.004	0.001	−0.003	0.002	0.079	−0.156	−0.004	−0.014
	(0.029)	(0.031)	(0.016)	(0.127)	(0.017)	(0.092)	(0.014)	(0.021)	(0.607)	(0.116)	(0.016)	(0.013)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.958	0.951	0.982	0.935	0.982	0.928	0.847	0.965	0.907	0.718	0.923	0.980
Panel B: Brown efficiency innovation												
L1 BROWNEFFRATIOEP	0.031	−0.045	−0.015	−0.241	−0.012	0.044	0.008	0.017	0.392	−0.072	0.007	−0.012
	(0.043)	(0.041)	(0.020)	(0.167)	(0.022)	(0.144)	(0.015)	(0.025)	(0.968)	(0.147)	(0.021)	(0.018)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.917	0.980
L3 BROWNEFFRATIOEP	0.051	−0.001	0.004	−0.105	0.003	−0.095	0.003	0.011	−0.945	−0.093	−0.004	0.006
	(0.037)	(0.038)	(0.020)	(0.110)	(0.021)	(0.135)	(0.013)	(0.022)	(0.761)	(0.125)	(0.018)	(0.016)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 BROWNEFFRATIOEP	0.065*	0.010	0.022		0.020	−0.067	−0.019*	0.004		0.170	0.025	0.029*
	(0.036)	(0.034)	(0.020)		(0.021)	(0.131)	(0.011)	(0.022)		(0.130)	(0.017)	(0.017)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.971	0.933	0.981		0.888	0.956	0.989
L1 3YEARAVGBROWNEFFRATIOEP	0.151***	−0.027	0.012	−0.136	0.028	0.095	0.004	0.024	−1.373	−0.014	−0.005	0.025
	(0.049)	(0.049)	(0.024)	(0.223)	(0.027)	(0.190)	(0.018)	(0.031)	(1.354)	(0.224)	(0.024)	(0.023)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.958	0.951	0.982	0.935	0.982	0.928	0.847	0.965	0.907	0.718	0.923	0.980
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.9. Patent Ratios and GICS-6 Industry-Level Outcomes

The unit of observation is GICS-6 industry-year and the sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years for the Trucost sample. In Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry. The key explanatory variables of interest are *GREENRATIOEP* in Panel A and *BROWNEFFRATIOEP* in Panel B. Controls include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either industry level logs of sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: GREENRATIOEP on all firms											
L1 GREENRATIOEP	0.117	0.327*	−0.084	0.073	−0.192	0.195**	−0.289**	1.249	0.001*	0.022	−0.006
	(0.174)	(0.180)	(0.092)	(0.497)	(1.106)	(0.097)	(0.131)	(3.118)	(0.001)	(0.061)	(0.087)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.962	0.932	0.959	0.961	0.988	0.734	0.976	0.842	0.911	0.924	0.936
L3 GREENRATIOEP	0.208	0.321**	−0.003	−1.005	−2.647**	0.264**	−0.339***	−2.551	0.001	0.016	0.085
	(0.156)	(0.129)	(0.081)	(0.915)	(1.207)	(0.111)	(0.114)	(2.939)	(0.001)	(0.057)	(0.080)
Observations	837	837	837	122	837	837	837	122	837	837	837
R2	0.981	0.978	0.990	0.990	0.994	0.784	0.988	0.974	0.957	0.984	0.986
L5 GREENRATIOEP	0.191	0.274***	−0.009		−1.562*	0.191*	−0.153*		0.001	−0.030	0.046
	(0.139)	(0.102)	(0.075)		(0.796)	(0.110)	(0.089)		(0.001)	(0.047)	(0.070)
Observations	708	708	708		708	708	708		708	708	708
R2	0.986	0.986	0.991		0.997	0.852	0.993		0.966	0.984	0.987
L1 3YEARAVGGREENRATIOEP	0.435*	1.273***	0.138	−1.699	−5.143**	0.660***	−0.679***	−7.100	0.003*	0.336*	0.308*
	(0.241)	(0.326)	(0.169)	(1.398)	(2.285)	(0.211)	(0.209)	(10.840)	(0.002)	(0.186)	(0.158)
Observations	988	988	988	267	988	988	988	267	988	988	988
R2	0.962	0.933	0.960	0.967	0.989	0.735	0.977	0.843	0.904	0.914	0.937
Panel A.2: GREENRATIOEP on ever patenting firms											
L1 GREENRATIOEP	−0.257	0.212	−0.146	0.567	−1.984	0.230*	−0.260**	1.521	0.001*	0.045	−0.037
	(0.224)	(0.199)	(0.121)	(0.822)	(1.491)	(0.122)	(0.108)	(3.659)	(0.001)	(0.072)	(0.125)
Observations	974	974	974	261	974	974	974	261	974	974	974
R2	0.962	0.960	0.984	0.954	0.926	0.679	0.973	0.695	0.955	0.979	0.981
L3 GREENRATIOEP	−0.206	0.294	−0.087	−0.388	−4.062**	0.347**	−0.359***	−4.782	0.001**	0.007	0.067
	(0.223)	(0.197)	(0.100)	(0.931)	(1.993)	(0.172)	(0.097)	(7.610)	(0.001)	(0.071)	(0.109)
Observations	834	834	834	122	834	834	834	122	834	834	834
R2	0.976	0.973	0.988	0.986	0.954	0.741	0.984	0.936	0.967	0.982	0.986
L5 GREENRATIOEP	−0.122	0.223	−0.098		−0.574	0.225	−0.193**		0.001*	−0.032	0.005
	(0.243)	(0.171)	(0.100)		(1.489)	(0.152)	(0.088)		(0.000)	(0.059)	(0.108)
Observations	705	705	705		705	705	705		705	705	705
R2	0.982	0.982	0.991		0.970	0.824	0.989		0.975	0.986	0.988
L1 3YEARAVGGREENRATIOEP	−0.416	0.938***	−0.076	−0.218	−6.652**	0.697**	−0.657***	−8.575	0.002	0.126	0.181
	(0.310)	(0.352)	(0.174)	(1.847)	(3.294)	(0.293)	(0.196)	(12.070)	(0.001)	(0.124)	(0.191)
Observations	985	985	985	265	985	985	985	265	985	985	985
R2	0.963	0.962	0.984	0.956	0.928	0.683	0.974	0.695	0.950	0.979	0.982
Panel A.3: GREENRATIOEP on never patenting firms											
L1 GREENRATIOEP	−0.068	0.384*	−0.144	0.168	1.701	0.229**	−0.403**	2.908	0.001	0.006	−0.048
	(0.171)	(0.200)	(0.105)	(0.451)	(1.419)	(0.106)	(0.192)	(2.700)	(0.002)	(0.068)	(0.096)
Observations	964	964	964	261	964	964	964	261	964	964	964
R2	0.941	0.921	0.940	0.972	0.980	0.735	0.630	0.959	0.794	0.938	0.939
L3 GREENRATIOEP	0.127	0.088	−0.050	0.040	−0.835	0.122*	−0.333**	−1.203	0.002	0.004	0.017
	(0.149)	(0.121)	(0.101)	(0.424)	(1.057)	(0.071)	(0.151)	(3.143)	(0.001)	(0.073)	(0.088)
Observations	819	819	819	122	819	819	819	122	819	819	819
R2	0.960	0.948	0.961	0.998	0.993	0.846	0.860	0.996	0.824	0.958	0.960
L5 GREENRATIOEP	0.100	−0.025	−0.066		−1.051	0.088	−0.139		0.001	−0.096	−0.037
	(0.148)	(0.133)	(0.103)		(0.680)	(0.080)	(0.128)		(0.001)	(0.084)	(0.093)
Observations	685	685	685		685	685	685		685	685	685
R2	0.973	0.959	0.967		0.996	0.898	0.929		0.866	0.963	0.966
L1 3YEARAVGGREENRATIOEP	0.110	0.977***	−0.033	−0.303	−1.057	0.437***	−0.823**	6.390	0.005*	0.113	0.064
	(0.276)	(0.349)	(0.215)	(1.072)	(1.746)	(0.154)	(0.362)	(5.121)	(0.003)	(0.138)	(0.191)
Observations	976	976	976	267	976	976	976	267	976	976	976
R2	0.941	0.920	0.939	0.974	0.979	0.736	0.631	0.959	0.793	0.932	0.937
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: BROWNEFFRATIOEP on all firms											
L1 BROWNEFFRATIOEP	−0.082	−0.365	−0.097	1.501	8.373**	−0.184	0.649*	43.304	0.000	−0.134	−0.144
	(0.185)	(0.383)	(0.146)	(2.008)	(3.554)	(0.210)	(0.387)	(41.529)	(0.001)	(0.092)	(0.112)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.962	0.932	0.959	0.961	0.989	0.734	0.976	0.853	0.911	0.924	0.936
L3 BROWNEFFRATIOEP	−0.138	−0.323	−0.228*	2.308	7.251***	−0.069	0.284	23.340	0.000	−0.155*	−0.167*
	(0.175)	(0.247)	(0.127)	(2.795)	(2.645)	(0.227)	(0.315)	(29.000)	(0.001)	(0.091)	(0.095)
Observations	837	837	837	122	837	837	837	122	837	837	837
R2	0.981	0.978	0.990	0.990	0.995	0.782	0.988	0.974	0.957	0.984	0.986
L5 BROWNEFFRATIOEP	0.146	−0.148	−0.142		1.564	0.015	−0.278		0.000	0.001	0.018
	(0.179)	(0.192)	(0.126)		(2.466)	(0.249)	(0.227)		(0.001)	(0.114)	(0.120)
Observations	708	708	708		708	708	708		708	708	708
R2	0.986	0.985	0.991		0.997	0.852	0.993		0.966	0.984	0.987
L1 3YEARAVGBROWNEFFRATIOEP	−0.104	−0.540	−0.130	6.213**	13.254***	−0.183	0.724**	96.369	−0.001	−0.211	−0.166
	(0.245)	(0.380)	(0.171)	(2.568)	(4.362)	(0.191)	(0.359)	(69.150)	(0.001)	(0.139)	(0.159)
Observations	988	988	988	267	988	988	988	267	988	988	988
R2	0.962	0.931	0.960	0.968	0.990	0.733	0.976	0.864	0.903	0.914	0.937
Panel B.2: BROWNEFFRATIOEP on ever patenting firms											
L1 BROWNEFFRATIOEP	0.288	−0.260	−0.078	0.435	13.008**	−0.199	0.573**	82.622	0.002*	0.075	−0.241
	(0.268)	(0.532)	(0.187)	(2.965)	(6.495)	(0.260)	(0.270)	(69.540)	(0.001)	(0.106)	(0.228)
Observations	974	974	974	261	974	974	974	261	974	974	974
R2	0.962	0.960	0.984	0.954	0.932	0.679	0.973	0.727	0.954	0.979	0.981
L3 BROWNEFFRATIOEP	0.094	−0.230	−0.220*	1.391	8.228	−0.182	0.211	24.203	0.001	0.128	−0.235
	(0.251)	(0.397)	(0.115)	(2.703)	(5.915)	(0.301)	(0.200)	(36.508)	(0.001)	(0.097)	(0.149)
Observations	834	834	834	122	834	834	834	122	834	834	834
R2	0.976	0.973	0.988	0.986	0.955	0.740	0.984	0.937	0.967	0.982	0.986
L5 BROWNEFFRATIOEP	0.192	−0.175	−0.151		−4.654	−0.029	−0.308*		0.000	0.183**	0.018
	(0.303)	(0.303)	(0.118)		(3.254)	(0.269)	(0.169)		(0.001)	(0.088)	(0.150)
Observations	705	705	705		705	705	705		705	705	705
R2	0.982	0.982	0.991		0.970	0.824	0.989		0.975	0.986	0.988
L1 3YEARAVGBROWNEFFRATIOEP	−0.106	−0.493	−0.199	9.066**	17.600**	−0.227	0.675**	191.709	0.001	0.184	−0.396
	(0.466)	(0.592)	(0.241)	(4.014)	(8.717)	(0.243)	(0.330)	(131.078)	(0.002)	(0.135)	(0.283)
Observations	985	985	985	265	985	985	985	265	985	985	985
R2	0.963	0.961	0.984	0.959	0.934	0.681	0.973	0.754	0.950	0.979	0.982
Panel B.3: BROWNEFFRATIOEP on never patenting firms											
L1 BROWNEFFRATIOEP	−0.295	−0.728*	−0.113	−0.495	3.302	−0.383**	0.251	−10.842	−0.003	−0.133	−0.087
	(0.285)	(0.391)	(0.234)	(1.423)	(2.278)	(0.177)	(0.583)	(8.039)	(0.003)	(0.140)	(0.170)
Observations	964	964	964	261	964	964	964	261	964	964	964
R2	0.941	0.921	0.940	0.972	0.980	0.735	0.629	0.959	0.794	0.938	0.939
L3 BROWNEFFRATIOEP	−0.585**	−0.712***	−0.467**	−0.109	4.589**	−0.030	0.082	3.322	0.000	−0.275*	−0.278
	(0.268)	(0.263)	(0.231)	(0.761)	(2.047)	(0.142)	(0.417)	(5.100)	(0.003)	(0.143)	(0.174)
Observations	819	819	819	122	819	819	819	122	819	819	819
R2	0.960	0.948	0.961	0.998	0.993	0.846	0.860	0.996	0.824	0.958	0.960
L5 BROWNEFFRATIOEP	−0.615**	−0.655**	−0.675***		2.368	−0.100	−0.404		0.002	−0.319*	−0.374*
	(0.260)	(0.275)	(0.210)		(1.838)	(0.148)	(0.289)		(0.003)	(0.166)	(0.198)
Observations	685	685	685		685	685	685		685	685	685
R2	0.973	0.959	0.967		0.996	0.898	0.929		0.866	0.963	0.966
L1 3YEARAVGBROWNEFFRATIOEP	−0.790**	−1.274***	−0.489*	1.409	8.154*	−0.332*	0.006	−2.571	−0.004	−0.321*	−0.247
	(0.402)	(0.405)	(0.276)	(1.611)	(4.320)	(0.170)	(0.616)	(10.075)	(0.004)	(0.193)	(0.204)
Observations	976	976	976	267	976	976	976	267	976	976	976
R2	0.941	0.920	0.940	0.974	0.980	0.735	0.630	0.959	0.793	0.932	0.937
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.10. Patent Ratios and Cross-Industry Outcomes

The unit of observation is GICS-8 industry-year. The sample period is 2005 to 2020. We aggregate the dependent variables at a given GICS-8 industry's higher GICS-2 level including all GICS-8 industries but the given GICS-8 industry used for the independent variables. The dependent variables are thus GICS-2 industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively GICS-2 industry level cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A.1 and B1., dependent variables are calculated across all firms in the broader GICS-2 industry except the given GICS-8 industry. In Panel A.2 and B.2, dependent variables are similarly calculated only for ever-patenting firms and in Panel A.3 and B.3 only for never-patenting firms. In Panel A, the key independent variable of interest is the GICS-8 industry level GREENRATIOEP and in Panel B the GICS-8 industry level BROWNEFFRATIOEP. Controls at the GICS-8 all firms (ever-patenting, respectively never patenting) level include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either GICS-8 industry level logs of sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-8 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: GREENRATIOEP on all firms											
L1 GREENRATIOEP/100	0.274	1.152	−7.787**	−0.381	18.915	3.968*	−1.746	−24.219	0.005	−2.646	−6.478*
	(4.448)	(4.302)	(3.592)	(13.828)	(20.521)	(2.174)	(3.815)	(87.962)	(0.016)	(1.647)	(3.573)
Observations	1958	1958	1958	561	1958	1958	1958	561	1958	1958	1958
R2	0.986	0.972	0.985	0.982	0.989	0.976	0.983	0.964	0.957	0.982	0.966
L3 GREENRATIOEP/100	6.055*	4.386	−1.757	0.409	4.019	3.694*	0.193	−57.379	−0.007	−1.278	−0.288
	(3.639)	(3.466)	(3.450)	(8.701)	(15.199)	(1.920)	(2.905)	(87.317)	(0.018)	(1.441)	(3.596)
Observations	1649	1649	1649	262	1649	1649	1649	262	1649	1649	1649
R2	0.993	0.984	0.989	0.997	0.993	0.983	0.991	0.995	0.969	0.987	0.974
L5 GREENRATIOEP/100	6.013	7.693**	1.466		9.338	3.574*	−0.715		−0.009	−1.256	2.251
	(3.874)	(3.214)	(3.532)		(14.879)	(2.119)	(2.763)		(0.017)	(1.379)	(3.551)
Observations	1363	1363	1363		1363	1363	1363		1363	1363	1363
R2	0.995	0.990	0.992		0.995	0.989	0.995		0.979	0.991	0.981
L1 3YEARAVGGREENRATIOEP	0.049	0.167**	−0.069	−0.474**	−0.237	0.097***	−0.116**	−4.151***	−0.000	−0.028	−0.020
	(0.064)	(0.068)	(0.055)	(0.203)	(0.309)	(0.029)	(0.058)	(1.430)	(0.000)	(0.025)	(0.056)
Observations	2065	2065	2065	589	2065	2065	2065	589	2065	2065	2065
R2	0.986	0.972	0.985	0.982	0.989	0.976	0.983	0.965	0.956	0.982	0.966
Panel A.2: GREENRATIOEP on ever-patenting firms											
L1 GREENRATIOEP/100	−3.978	1.691	−8.359***	−7.007	−45.317*	4.770*	−3.065	−148.941	0.007	−3.186	−7.948**
	(6.353)	(4.376)	(3.083)	(18.423)	(27.009)	(2.491)	(4.517)	(139.989)	(0.012)	(2.003)	(3.180)
Observations	1949	1949	1949	558	1949	1949	1949	558	1949	1949	1949
R2	0.979	0.975	0.989	0.972	0.971	0.968	0.980	0.903	0.967	0.982	0.974
L3 GREENRATIOEP/100	5.368	2.574	−5.273**	−6.927	−28.576*	3.857	−2.080	−90.323	−0.001	−4.267**	−3.135
	(5.636)	(3.783)	(2.670)	(12.794)	(15.220)	(2.412)	(3.515)	(117.378)	(0.012)	(2.011)	(2.997)
Observations	1640	1640	1640	262	1640	1640	1640	262	1640	1640	1640
R2	0.988	0.984	0.993	0.993	0.985	0.976	0.989	0.985	0.976	0.986	0.981
L5 GREENRATIOEP/100	1.362	4.321	−4.812*		−21.360	3.715	−4.175		−0.006	−4.868**	−1.294
	(6.032)	(3.079)	(2.770)		(17.893)	(2.502)	(3.455)		(0.012)	(2.053)	(2.948)
Observations	1353	1353	1353		1353	1353	1353		1353	1353	1353
R2	0.992	0.991	0.995		0.992	0.984	0.994		0.985	0.990	0.985
L1 3YEARAVGGREENRATIOEP	−0.039	0.088	−0.134***	−0.682**	−1.471***	0.075**	−0.171**	−7.135**	−0.000	−0.094***	−0.065
	(0.095)	(0.064)	(0.048)	(0.337)	(0.390)	(0.032)	(0.071)	(2.909)	(0.000)	(0.030)	(0.048)
Observations	2053	2053	2053	584	2053	2053	2053	584	2053	2053	2053
R2	0.979	0.976	0.990	0.971	0.972	0.968	0.980	0.902	0.967	0.984	0.977
Panel A.3: GREENRATIOEP on never-patenting firms											
L1 GREENRATIOEP/100	2.807	−1.513	−4.849	−6.752	48.319	0.381	3.234	15.569	−0.016	−2.543	−6.171
	(6.418)	(6.789)	(4.666)	(8.003)	(38.510)	(4.259)	(4.524)	(71.305)	(0.043)	(2.830)	(3.832)
Observations	1901	1901	1901	561	1901	1901	1901	561	1901	1901	1901
R2	0.971	0.940	0.970	0.993	0.987	0.965	0.978	0.993	0.923	0.964	0.961
L3 GREENRATIOEP/100	9.768*	0.179	2.869	−2.011	22.789	1.462	3.915	−75.320	−0.083**	−1.346	1.827
	(5.355)	(5.988)	(4.508)	(5.221)	(34.406)	(2.154)	(3.990)	(52.497)	(0.041)	(2.461)	(3.795)
Observations	1579	1579	1579	262	1579	1579	1579	262	1579	1579	1579
R2	0.984	0.954	0.977	0.999	0.992	0.988	0.985	0.999	0.953	0.970	0.968
L5 GREENRATIOEP/100	9.663**	0.665	3.754		33.909	1.466	−0.088		−0.053	−2.322	3.194
	(4.820)	(5.306)	(4.758)		(34.028)	(2.037)	(4.106)		(0.038)	(2.586)	(3.984)
Observations	1285	1285	1285		1285	1285	1285		1285	1285	1285
R2	0.992	0.963	0.982		0.994	0.994	0.992		0.973	0.976	0.975
L1 3YEARAVGGREENRATIOEP	0.172	0.159	0.019	−0.557***	0.729	0.100	−0.005	−4.192***	−0.002***	−0.044	0.012
	(0.107)	(0.112)	(0.074)	(0.161)	(0.536)	(0.070)	(0.070)	(1.185)	(0.001)	(0.041)	(0.060)
Observations	2006	2006	2006	589	2006	2006	2006	589	2006	2006	2006
R2	0.971	0.940	0.970	0.993	0.988	0.965	0.977	0.993	0.924	0.963	0.961
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: BROWNEFFRATIOEP on all firms											
L1 BROWNEFFRATIOEP/100	−2.188	3.363	6.716	−9.622	39.080	2.628	8.503	−219.445	−0.034	−0.060	6.925
	(6.250)	(8.202)	(5.807)	(32.729)	(50.465)	(4.144)	(9.709)	(234.536)	(0.025)	(3.624)	(5.957)
Observations	1958	1958	1958	561	1958	1958	1958	561	1958	1958	1958
R2	0.986	0.972	0.985	0.982	0.989	0.976	0.983	0.964	0.957	0.982	0.966
L3 BROWNEFFRATIOEP/100	−2.626	5.427	1.591	30.222	44.805	4.714	3.224	62.765	−0.013	0.681	2.981
	(5.124)	(5.862)	(5.337)	(20.141)	(37.907)	(3.383)	(7.785)	(248.948)	(0.024)	(3.281)	(5.355)
Observations	1649	1649	1649	262	1649	1649	1649	262	1649	1649	1649
R2	0.993	0.984	0.989	0.997	0.993	0.983	0.991	0.995	0.969	0.987	0.974
L5 BROWNEFFRATIOEP/100	−3.082	3.236	1.976		30.790	−0.465	3.151		−0.043**	0.853	3.844
	(4.496)	(4.740)	(5.199)		(28.161)	(2.502)	(4.550)		(0.020)	(2.327)	(5.216)
Observations	1363	1363	1363		1363	1363	1363		1363	1363	1363
R2	0.995	0.990	0.992		0.995	0.989	0.995		0.979	0.991	0.981
L1 3YEARAVGBROWNEFFRATIOEP	−0.036	−0.015	0.051	0.382**	1.661***	0.024	0.077	1.320	−0.000	0.036	0.079
	(0.083)	(0.105)	(0.077)	(0.162)	(0.632)	(0.063)	(0.113)	(2.356)	(0.000)	(0.040)	(0.071)
Observations	2065	2065	2065	589	2065	2065	2065	589	2065	2065	2065
R2	0.986	0.972	0.985	0.981	0.989	0.976	0.983	0.964	0.956	0.982	0.966
Panel B.2: BROWNEFFRATIOEP on ever-patenting firms											
L1 BROWNEFFRATIOEP/100	−0.658	9.914	9.224*	−7.806	67.476	5.614	9.864	−165.991	−0.006	1.267	9.585*
	(7.179)	(8.810)	(5.575)	(41.345)	(52.164)	(4.597)	(10.708)	(310.706)	(0.018)	(4.037)	(5.638)
Observations	1949	1949	1949	558	1949	1949	1949	558	1949	1949	1949
R2	0.979	0.975	0.989	0.972	0.971	0.968	0.980	0.903	0.967	0.982	0.974
L3 BROWNEFFRATIOEP/100	−4.455	6.194	0.886	25.638	25.937	5.418	4.176	208.613	0.005	1.386	3.324
	(5.905)	(7.620)	(5.421)	(22.319)	(38.253)	(4.025)	(8.566)	(296.275)	(0.015)	(4.182)	(5.227)
Observations	1640	1640	1640	262	1640	1640	1640	262	1640	1640	1640
R2	0.988	0.984	0.993	0.993	0.985	0.976	0.989	0.985	0.976	0.986	0.981
L5 BROWNEFFRATIOEP/100	−5.222	2.829	−0.121		4.514	−0.498	3.030		−0.011	1.877	3.485
	(5.042)	(5.053)	(5.000)		(29.609)	(2.838)	(5.168)		(0.012)	(3.904)	(5.005)
Observations	1353	1353	1353		1353	1353	1353		1353	1353	1353
R2	0.992	0.991	0.995		0.992	0.984	0.994		0.985	0.990	0.985
L1 3YEARAVGBROWNEFFRATIOEP	−0.015	0.141	0.067	0.260	1.652**	0.134***	0.098	2.303	−0.000	0.017	0.109
	(0.111)	(0.101)	(0.081)	(0.248)	(0.690)	(0.050)	(0.127)	(2.823)	(0.000)	(0.050)	(0.070)
Observations	2053	2053	2053	584	2053	2053	2053	584	2053	2053	2053
R2	0.979	0.976	0.990	0.970	0.972	0.968	0.980	0.899	0.967	0.984	0.977
Panel B.3: BROWNEFFRATIOEP on never-patenting firms											
L1 BROWNEFFRATIOEP/100	6.986	−1.889	12.488	−17.850	16.222	−3.298	10.079	−309.372	−0.112	1.836	10.825
	(14.793)	(15.539)	(8.499)	(15.141)	(76.488)	(10.258)	(8.781)	(241.999)	(0.078)	(5.863)	(6.996)
Observations	1901	1901	1901	561	1901	1901	1901	561	1901	1901	1901
R2	0.971	0.940	0.970	0.993	0.987	0.965	0.978	0.993	0.923	0.964	0.961
L3 BROWNEFFRATIOEP/100	0.705	6.288	6.648	−12.721	−27.280	1.284	3.952	−171.316	−0.043	1.270	5.746
	(10.829)	(11.021)	(8.563)	(12.774)	(64.711)	(5.104)	(8.204)	(219.561)	(0.072)	(5.887)	(6.651)
Observations	1579	1579	1579	262	1579	1579	1579	262	1579	1579	1579
R2	0.984	0.954	0.977	0.999	0.992	0.988	0.985	0.999	0.953	0.970	0.968
L5 BROWNEFFRATIOEP/100	−7.126	−2.038	0.479		−2.111	−2.379	4.280		−0.090	−2.578	0.036
	(8.393)	(9.430)	(9.103)		(57.376)	(3.130)	(5.925)		(0.057)	(4.938)	(6.932)
Observations	1285	1285	1285		1285	1285	1285		1285	1285	1285
R2	0.992	0.963	0.982		0.994	0.994	0.992		0.973	0.976	0.975
L1 3YEARAVGBROWNEFFRATIOEP	0.061	−0.253	0.108	0.150	1.150	−0.226	0.071	1.519	−0.001	0.070	0.107
	(0.164)	(0.205)	(0.109)	(0.117)	(0.958)	(0.153)	(0.106)	(2.395)	(0.001)	(0.065)	(0.085)
Observations	2006	2006	2006	589	2006	2006	2006	589	2006	2006	2006
R2	0.971	0.940	0.970	0.993	0.988	0.965	0.977	0.993	0.924	0.963	0.961
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.13. Patent Ratios and Firm-Level Market Share

The unit of observation is firm-year and covers both public and private firms, as we do not rely on public firms' emission data. The sample period is 2005 to 2020. The dependent variable is MKTSHR GICS6, which is a firm's market share based on its sales relative to total public and private firms' sales in a given GICS6 industry. The key dependent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years in columns 1 to 3 and *BROWNEFFRATIOEP* lagged by 1, 3 or 5 years in column 4 to 6. Controls include: *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *INVEST/A*, and, *PUBLIC*. *LOGASSETS* is the log of total assets in million USD and *PUBLIC* is an indicator equal to 1 for public firms. All other variables are defined in Table 3.1 and Table 3.2. All independent variables are lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. In Panel A we include country and GICS6 industry-year fixed effects and in Panel B firm and year fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	MKTSHR GICS6					
Panel A: Country and Industry-Year Fixed Effects						
L1 GREENRATIOEP	-0.076^{***}					
	(0.028)					
L3 GREENRATIOEP		-0.070^{**}				
		(0.032)				
L5 GREENRATIOEP			-0.122^{***}			
			(0.043)			
L1 BROWNEFFRATIOEP				0.034		
				(0.049)		
L3 BROWNEFFRATIOEP					0.028	
					(0.053)	
L5 BROWNEFFRATIOEP						-0.010
						(0.067)
Observations	44202	34043	25036	44202	34043	25036
R2	0.462	0.469	0.477	0.461	0.469	0.477
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
GICS6-Year F.E.	yes	yes	yes	yes	yes	yes
Panel B: Firm and Year Fixed Effects						
L1 GREENRATIOEP	-0.025					
	(0.021)					
L3 GREENRATIOEP		-0.046^{*}				
		(0.025)				
L5 GREENRATIOEP			-0.042			
			(0.029)			
L1 BROWNEFFRATIOEP				0.017		
				(0.042)		
L3 BROWNEFFRATIOEP					0.040	
					(0.037)	
L5 BROWNEFFRATIOEP						-0.012
						(0.046)
Observations	43346	33147	24189	43346	33147	24189
R2	0.869	0.887	0.903	0.869	0.887	0.903
Controls	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes

Table 3.14. Ex-post characteristics of emission decreasing vs increasing firms

The unit of observation is firm-year and the sample period is 2005 to 2020. Panel A covers total scope 1 emissions. To split firms in emission reduction samples (column 1 to 4) and emission increase samples (column 5 to 8) we calculate changes in emissions over three years. Panel B defines emission reduction firms as those that decreased emissions across scope 1, 2 and upstream 3 and emission increase firms as all others. We calculate mean, standard deviation, median and the count for each sample as well as the difference and p-value between the two samples for a variety of variables at the three year lag. Panel A.1 and B.1 cover the full Trucost sample. Panel A.2 and B.2 zoom in on the Trucost sample with at least one patent at the European Patent Office and the greatest emission change. Within the emission decrease sample, we focus on the 50% with the greatest emission decrease. Similarly within the emission increase sample, we focus on the 50% with the greatest emission increase. DUMMYANYEP (DUMMYGREENEP, DUMMYBROWNEFFEP, and DUMMYOECDEP) are dummies equal to one if a firm has at least one (one green, one brown efficiency and one OECD env-tech) patent and zero otherwise. SALES3YRCHG is the change in sales across the three year period in decimals. All other variables are defined in Table 3.1, Table 3.2 and Table 3.4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Emission decrease sample				Emission increase sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: 3-year changes in scope 1 emissions										
Panel A.1: Patenting and non-patenting firms										
DUMMYANYEP	0.310	0.463	0.000	32068	0.280	0.449	0.000	39100	0.030	0.000
DUMMYGREENEP	0.149	0.356	0.000	32068	0.116	0.321	0.000	39100	0.032	0.000
DUMMYBROWNEFFEP	0.069	0.253	0.000	32068	0.054	0.226	0.000	39100	0.015	0.000
DUMMYOECDEP	0.154	0.361	0.000	32068	0.120	0.324	0.000	39100	0.035	0.000
AGE	47.252	38.678	34.000	29809	41.075	35.860	28.000	36468	6.177	0.000
LOGSIZE	7.752	1.667	7.782	32068	7.665	1.565	7.722	39100	0.086	0.000
LOGPPE	6.055	2.336	6.237	32068	5.794	2.298	5.980	39100	0.261	0.000
MB	2.373	2.676	1.588	32068	2.826	2.962	1.903	39100	−0.453	0.000
LEVERAGE	23.937	17.967	22.294	32068	23.249	18.279	21.290	39100	0.688	0.000
ROE	10.749	26.144	10.388	32068	11.872	23.995	11.544	39100	−1.123	0.000
SALES3YRCHG	−0.094	0.524	−0.024	32004	0.327	0.512	0.249	39034	−0.421	0.000
Panel A.2: Firm-years with at least one EP patent & greatest emission decreases, resp. increases										
GREENRATIOEP	11.944	23.526	0.000	4973	11.589	24.309	0.000	5478	0.355	0.449
BROWNEFFRATIOEP	3.776	13.151	0.000	4973	3.542	13.569	0.000	5478	0.234	0.371
OECDRATIOEP	13.354	24.952	0.000	4973	11.530	23.606	0.000	5478	1.823	0.000
GREENCITMAXEP	65.316	561.564	0.000	4973	56.955	532.163	0.000	5478	8.361	0.436
BROWNEFFCITMAXEP	14.912	210.829	0.000	4973	8.502	51.493	0.000	5478	6.410	0.037
GREENCOUNTBBEP	0.260	1.128	0.000	4973	0.195	1.007	0.000	5478	0.066	0.002
BROWNEFFCOUNTBBEP	0.107	0.834	0.000	4973	0.057	0.472	0.000	5478	0.049	0.000
AGE	55.569	41.713	44.000	4929	46.442	39.625	32.000	5443	9.127	0.000
LOGSIZE	8.365	1.589	8.363	4973	8.134	1.593	8.133	5478	0.231	0.000
LOGPPE	6.719	2.017	6.813	4973	6.169	2.151	6.312	5478	0.550	0.000
MB	2.609	2.714	1.837	4973	3.312	3.291	2.285	5478	−0.703	0.000
LEVERAGE	22.636	15.588	21.787	4973	22.143	16.984	21.209	5478	0.493	0.122
ROE	9.536	27.992	10.644	4973	9.088	28.816	11.344	5478	0.447	0.421
SALES3YRCHG	−0.110	0.553	−0.020	4968	0.429	0.599	0.350	5474	−0.539	0.000
Panel B: Ex-post characteristics of firms decreasing absolute emissions across scope 1, 2, and upstream 3										
Panel B.1: Patenting and non-patenting firms										
DUMMYANYEP	0.260	0.439	0.000	16298	0.304	0.460	0.000	54950	−0.044	0.000
DUMMYGREENEP	0.115	0.319	0.000	16298	0.136	0.342	0.000	54950	−0.021	0.000
DUMMYBROWNEFFEP	0.054	0.225	0.000	16298	0.063	0.242	0.000	54950	−0.009	0.000
DUMMYOECDEP	0.119	0.324	0.000	16298	0.140	0.347	0.000	54950	−0.020	0.000
AGE	44.742	37.286	32.000	15124	43.565	37.259	30.000	51227	1.177	0.001
LOGSIZE	7.411	1.690	7.461	16298	7.792	1.578	7.826	54950	−0.381	0.000
LOGPPE	5.697	2.406	5.863	16298	5.973	2.289	6.160	54950	−0.276	0.000
MB	2.244	2.588	1.509	16298	2.734	2.907	1.829	54950	−0.490	0.000
LEVERAGE	24.227	18.693	22.417	16298	23.357	17.968	21.546	54950	0.870	0.000
ROE	8.589	28.284	9.361	16298	12.192	23.852	11.467	54950	−3.603	0.000
SALES3YRCHG	−0.299	0.592	−0.168	16254	0.267	0.477	0.204	54864	−0.566	0.000
Panel B.2: Firm-years with at least one EP patent & greatest emission decreases, resp. increases										
GREENRATIOEP	12.232	24.679	0.000	2256	11.822	23.423	0.000	8469	0.410	0.478
BROWNEFFRATIOEP	4.187	14.338	0.000	2256	3.830	13.524	0.000	8469	0.357	0.288
OECDRATIOEP	13.448	25.767	0.000	2256	12.285	23.507	0.000	8469	1.163	0.052
GREENCITMAXEP	58.520	554.662	0.000	2256	69.971	789.631	0.000	8469	−11.451	0.429
BROWNEFFCITMAXEP	17.191	306.872	0.000	2256	10.717	52.799	0.000	8469	6.474	0.318
GREENCOUNTBBEP	0.236	1.090	0.000	2256	0.249	1.201	0.000	8469	−0.013	0.614
BROWNEFFCOUNTBBEP	0.116	0.996	0.000	2256	0.084	0.637	0.000	8469	0.032	0.147
AGE	54.519	42.417	43.000	2240	52.884	42.120	39.000	8406	1.634	0.105
LOGSIZE	8.096	1.722	8.086	2256	8.366	1.642	8.333	8469	−0.270	0.000
LOGPPE	6.470	2.300	6.690	2256	6.622	2.158	6.704	8469	−0.152	0.005
MB	2.402	2.613	1.711	2256	3.028	3.113	2.065	8469	−0.625	0.000
LEVERAGE	23.427	16.196	22.574	2256	22.937	16.493	22.141	8469	0.490	0.203
ROE	5.718	32.059	9.094	2256	10.529	27.509	11.311	8469	−4.810	0.000
SALES3YRCHG	−0.402	0.640	−0.258	2252	0.310	0.530	0.225	8465	−0.713	0.000

Table 3.15. Long Patent Ratios and Firm Level Outcomes

The unit of observation is firm-year. The dependent variables are DIFS1TOT, DIFS2TOT, DIFS3UPTOT, DIFS1INT, DIFS2INT, DIFS3UPINT, DIFCAPEX, DIFINVEST/A, and DIFSALES, which are differences between the 2015 to 2020 average and the 2005 to 2014 average for scope 1 (2 and upstream 3) total emission (in kilo tonnes), scope 1 (2 and upstream 3) intensities, capital expenditures (in million USD), investment/assets, and sales (in million USD). We winsorize all differences at the 2.5% and 97.5% level. In Panel A the key independent variable is a long cumulative green (brown efficiency) patent ratio from 1990 to 2004, respectively 1990 to 2014. In Panel B the key independent variable is similarly a long cumulative green (brown efficiency) patent count from 1990 to 2004, respectively 1990 to 2014. Control variables include $LOGSIZE$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $BETA$, $VOLAT$, MOM, RET, $MSCI$ and are averages between 2004 and 2014. Logarithmic values are first averaged before taking the logarithm. The model is estimated using pooled regression model. All regression include country and GICS-6 industry fixed effects. We cluster standard errors at the GICS-6 industry dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) DIFS1TOT	(2) DIFS2TOT	(3) DIFS3UPTOT	(4) DIFS1INT	(5) DIFS2INT	(6) DIFS3UPINT	(7) DIFCAPEX	(8) DIFINVEST/A	(9) DIFSALES
Panel A: Long patent ratios									
Panel A.1: Green innovation									
Panel A.1.1: GREENSTOCKRATIOEP between 1990 and 2004									
GREENSTOCKRATIOEP04	75.203	24.542	102.814	−0.013	−0.003	0.004	0.726	−0.039	55.272*
	(73.411)	(18.622)	(65.778)	(0.009)	(0.004)	(0.007)	(2.814)	(0.024)	(32.521)
Observations	1863	1863	1863	1863	1863	1863	1863	1863	1863
R2	0.157	0.227	0.215	0.179	0.197	0.0987	0.290	0.257	0.322
Panel A.1.2: GREENSTOCKRATIOEP between 1990 and 2014									
GREENSTOCKRATIOEP14	22.870	15.093	46.439	0.009	0.000	−0.001	−1.051	−0.057*	18.040
	(61.876)	(16.411)	(37.061)	(0.011)	(0.003)	(0.004)	(3.432)	(0.029)	(23.007)
Observations	2714	2714	2714	2714	2714	2714	2714	2714	2714
R2	0.158	0.202	0.197	0.157	0.178	0.0824	0.255	0.248	0.291
Panel A.2: Brown efficiency innovation									
Panel A.2.1: BROWNEFFSTOCKRATIOEP between 1990 and 2004									
BROWNEFFSTOCKRATIOEP04	128.610	0.391	−142.637	0.023	−0.002	−0.016*	1.110	0.071*	−13.470
	(169.306)	(33.097)	(136.552)	(0.014)	(0.005)	(0.008)	(4.697)	(0.039)	(45.198)
Observations	1863	1863	1863	1863	1863	1863	1863	1863	1863
R2	0.157	0.226	0.215	0.179	0.197	0.101	0.290	0.257	0.321
Panel A.2.2: BROWNEFFSTOCKRATIOEP between 1990 and 2014									
BROWNEFFSTOCKRATIOEP14	−91.677	−14.699	−104.420	0.011	−0.001	−0.022***	2.663	−0.019	73.016*
	(160.687)	(28.900)	(86.969)	(0.032)	(0.004)	(0.007)	(3.749)	(0.027)	(43.684)
Observations	2714	2714	2714	2714	2714	2714	2714	2714	2714
R2	0.159	0.202	0.197	0.157	0.178	0.0873	0.255	0.246	0.292
Panel B: Long patent counts									
Panel A.1: Green innovation									
Panel B.1.1: GREENSTOCKCOUNTEP between 1990 and 2004									
GREENSTOCKCOUNTEP04/100	−857.522**	−143.944	−917.436***	−0.014	−0.006	−0.015	−42.715*	−0.027	−454.207***
	(394.550)	(98.038)	(314.020)	(0.014)	(0.007)	(0.009)	(21.467)	(0.044)	(165.993)
Observations	1863	1863	1863	1863	1863	1863	1863	1863	1863
R2	0.166	0.229	0.227	0.179	0.197	0.0995	0.302	0.256	0.333
Panel B.1.2: GREENSTOCKCOUNTEP between 1990 and 2014									
GREENSTOCKCOUNTEP14/100	−189.156**	18.559	−79.415	−0.008*	0.001	−0.001	−3.661	−0.002	−40.203
	(74.718)	(22.162)	(63.528)	(0.004)	(0.001)	(0.002)	(3.434)	(0.013)	(31.730)
Observations	2714	2714	2714	2714	2714	2714	2714	2714	2714
R2	0.166	0.203	0.199	0.158	0.178	0.0825	0.257	0.246	0.293
Panel B.2: Brown efficiency innovation									
Panel B.2.1: BROWNEFFSTOCKCOUNTEP between 1990 and 2004									
BROWNEFFSTOCKCOUNTEP04/100	−702.922	−22.974	−1189.932*	0.038	−0.001	−0.062***	−55.714	−0.020	−344.058
	(867.095)	(183.041)	(601.951)	(0.064)	(0.014)	(0.017)	(34.163)	(0.087)	(255.757)
Observations	1863	1863	1863	1863	1863	1863	1863	1863	1863
R2	0.159	0.226	0.220	0.179	0.197	0.104	0.295	0.256	0.323
Panel B.2.2: BROWNEFFSTOCKCOUNTEP between 1990 and 2014									
BROWNEFFSTOCKCOUNTEP14/100	−291.154	3.107	−220.098	0.002	−0.001	−0.008*	−9.221	0.015	−73.058
	(251.204)	(53.174)	(178.476)	(0.016)	(0.003)	(0.004)	(9.044)	(0.023)	(79.393)
Observations	2714	2714	2714	2714	2714	2714	2714	2714	2714
R2	0.161	0.202	0.199	0.157	0.178	0.0833	0.257	0.246	0.292
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.11. Public and Private Patent Ratios and GICS-6 Industry-Level Outcomes

The unit of observation is GICS-6 industry-year and the sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years for the Trucost sample. In Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry. The key explanatory variables of interest are *GREENRATIOEPPUBLIC* and *GREENRATIOEPPRIVATE*, which are industry level patent ratios for all public firms respectively all private firms in a given industry. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. Independent variables are either industry level logs of sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the given industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: GREENRATIOEP on all firms											
L1 GREENRATIOEP PUBLIC	0.132	0.330	−0.118	−0.090	1.524	0.287*	−0.102	1.191	0.002**	0.035	−0.047
	(0.219)	(0.211)	(0.130)	(0.801)	(2.042)	(0.157)	(0.172)	(5.795)	(0.001)	(0.082)	(0.112)
L1 GREENRATIOEP PRIVATE	−0.083	0.145	−0.054	0.310	−0.284	0.368*	−0.030	8.751	0.001	−0.026	−0.051
	(0.158)	(0.206)	(0.141)	(0.374)	(0.583)	(0.219)	(0.093)	(8.431)	(0.001)	(0.125)	(0.144)
Observations	840	840	840	227	840	840	840	227	840	840	840
R2	0.963	0.929	0.960	0.962	0.989	0.739	0.981	0.843	0.908	0.926	0.936
L3 GREENRATIOEP PUBLIC	0.180	0.428***	−0.089	−3.676	−3.293*	0.483**	−0.407***	−12.702	0.002*	0.026	0.070
	(0.215)	(0.160)	(0.114)	(2.809)	(1.726)	(0.226)	(0.149)	(10.306)	(0.001)	(0.072)	(0.106)
L3 GREENRATIOEP PRIVATE	0.011	0.185**	−0.021	−0.986	0.552	0.321**	−0.023	−8.185	0.000	0.042	−0.004
	(0.082)	(0.088)	(0.040)	(0.747)	(0.513)	(0.154)	(0.071)	(7.646)	(0.000)	(0.039)	(0.045)
Observations	720	720	720	106	720	720	720	106	720	720	720
R2	0.981	0.977	0.990	0.991	0.995	0.787	0.990	0.974	0.958	0.985	0.986
L5 GREENRATIOEP PUBLIC	0.217	0.288*	−0.021		−0.985	0.244	−0.155		0.002*	−0.045	0.034
	(0.223)	(0.156)	(0.123)		(1.157)	(0.229)	(0.130)		(0.001)	(0.076)	(0.119)
L5 GREENRATIOEP PRIVATE	−0.053	0.170**	−0.041		0.511	0.332*	−0.038		0.000	0.067	−0.017
	(0.060)	(0.080)	(0.046)		(0.350)	(0.194)	(0.063)		(0.000)	(0.043)	(0.049)
Observations	606	606	606		606	606	606		606	606	606
R2	0.985	0.984	0.992		0.997	0.855	0.994		0.967	0.986	0.987
L1 3YEARAVGGREENRATIOEP PUBLIC	0.516	1.339***	0.139	−2.859	−6.385	0.806**	−0.565**	−21.035	0.002	0.325*	0.376**
	(0.324)	(0.334)	(0.208)	(2.322)	(4.415)	(0.336)	(0.282)	(24.789)	(0.002)	(0.181)	(0.183)
L1 3YEARAVGGREENRATIOEP	−0.547	−0.254	−0.378	1.647	0.656	0.510**	0.109	29.347	0.001	−0.378	−0.394
PRIVATE	(0.442)	(0.550)	(0.435)	(1.157)	(1.165)	(0.242)	(0.150)	(26.466)	(0.002)	(0.419)	(0.451)
Observations	874	874	874	239	874	874	874	239	874	874	874
R2	0.962	0.926	0.958	0.967	0.987	0.738	0.978	0.851	0.896	0.912	0.934
Panel A.2: GREENRATIOEP on ever patenting firms											
L1 GREENRATIOEP PUBLIC	−0.001	0.440*	−0.084	1.242	−1.304	0.418**	−0.244	3.074	0.001	0.127	0.010
	(0.333)	(0.264)	(0.178)	(1.110)	(2.743)	(0.205)	(0.154)	(6.872)	(0.001)	(0.087)	(0.164)
L1 GREENRATIOEP PRIVATE	0.016	0.122	−0.010	0.252	0.451	0.348	−0.075	15.399	0.001**	0.026	−0.001
	(0.098)	(0.143)	(0.054)	(0.491)	(0.730)	(0.271)	(0.095)	(13.646)	(0.000)	(0.040)	(0.062)
Observations	838	838	838	227	838	838	838	227	838	838	838
R2	0.962	0.960	0.985	0.958	0.926	0.686	0.977	0.700	0.948	0.981	0.982
L3 GREENRATIOEP PUBLIC	0.290	0.641***	0.026	−3.232	−7.870**	0.650**	−0.489***	−22.143	0.002**	0.107	0.224
	(0.361)	(0.240)	(0.156)	(3.137)	(3.778)	(0.298)	(0.136)	(24.102)	(0.001)	(0.100)	(0.137)
L3 GREENRATIOEP PRIVATE	0.018	0.175	−0.075	−0.877	0.986	0.322*	−0.102	−9.633	0.000	0.005	−0.055
	(0.147)	(0.138)	(0.077)	(0.796)	(0.943)	(0.188)	(0.080)	(12.253)	(0.000)	(0.044)	(0.076)
Observations	717	717	717	106	717	717	717	106	717	717	717
R2	0.974	0.972	0.989	0.989	0.956	0.744	0.988	0.937	0.965	0.984	0.986
L5 GREENRATIOEP PUBLIC	0.419	0.346	0.121		−1.931	0.305	−0.103		0.001	0.000	0.134
	(0.325)	(0.224)	(0.118)		(3.779)	(0.288)	(0.127)		(0.001)	(0.091)	(0.129)
L5 GREENRATIOEP PRIVATE	−0.083	0.146	−0.094		0.046	0.384*	−0.056		0.000	−0.011	−0.089
	(0.096)	(0.103)	(0.058)		(0.944)	(0.229)	(0.070)		(0.000)	(0.042)	(0.066)
Observations	605	605	605		605	605	605		605	605	605
R2	0.981	0.981	0.992		0.969	0.827	0.993		0.977	0.987	0.989
L1 3YEARAVGGREENRATIOEP PUBLIC	0.410	1.604***	0.266	−1.455	−19.084**	1.021**	−0.947***	−37.079	0.001	0.378***	0.571**
	(0.437)	(0.456)	(0.272)	(2.957)	(7.825)	(0.451)	(0.285)	(34.085)	(0.001)	(0.140)	(0.289)
L1 3YEARAVGGREENRATIOEP	−0.140	0.366	−0.071	1.895	−0.504	0.594**	−0.174	60.707	0.001	0.037	0.001
PRIVATE	(0.160)	(0.225)	(0.095)	(1.650)	(2.192)	(0.296)	(0.153)	(46.638)	(0.001)	(0.059)	(0.100)
Observations	871	871	871	237	871	871	871	237	871	871	871
R2	0.961	0.959	0.985	0.955	0.902	0.687	0.977	0.730	0.947	0.981	0.982
Panel A.3: GREENRATIOEP on never patenting firms											
L1 GREENRATIOEP PUBLIC	−0.036	0.238	−0.074	0.138	2.782	0.239*	−0.100	5.491	0.001	−0.011	0.032
	(0.225)	(0.219)	(0.149)	(0.602)	(2.351)	(0.138)	(0.192)	(3.701)	(0.002)	(0.109)	(0.137)
L1 GREENRATIOEP PRIVATE	−0.058	0.405*	0.098	0.461	−0.075	0.249**	0.134	−0.577	−0.000	−0.052	0.045
	(0.174)	(0.213)	(0.141)	(0.292)	(0.699)	(0.110)	(0.088)	(1.732)	(0.001)	(0.147)	(0.143)
Observations	834	834	834	227	834	834	834	227	834	834	834
R2	0.948	0.928	0.945	0.974	0.990	0.755	0.958	0.961	0.765	0.944	0.940
L3 GREENRATIOEP PUBLIC	−0.075	−0.052	−0.167	−0.362	−0.748	0.199	−0.413*	−7.023	0.003	−0.037	−0.044
	(0.241)	(0.210)	(0.174)	(1.001)	(1.423)	(0.151)	(0.221)	(6.421)	(0.002)	(0.134)	(0.151)
L3 GREENRATIOEP PRIVATE	0.186	0.182	0.077	−0.248	0.558	0.230**	0.166	−3.903*	0.001	0.069	0.069
	(0.178)	(0.132)	(0.098)	(0.272)	(0.622)	(0.116)	(0.360)	(2.069)	(0.002)	(0.080)	(0.080)
Observations	710	710	710	106	710	710	710	106	710	710	710
R2	0.961	0.950	0.963	0.998	0.993	0.851	0.859	0.996	0.799	0.960	0.960
L5 GREENRATIOEP PUBLIC	−0.019	−0.225	−0.120		−0.375	0.008	−0.233		0.003	−0.145	−0.042
	(0.277)	(0.222)	(0.207)		(1.051)	(0.127)	(0.236)		(0.002)	(0.149)	(0.178)
L5 GREENRATIOEP PRIVATE	−0.043	0.040	−0.066		0.612	0.183	−0.205		0.003*	0.070	−0.012
	(0.162)	(0.135)	(0.107)		(0.429)	(0.111)	(0.199)		(0.002)	(0.084)	(0.088)
Observations	594	594	594		594	594	594		594	594	594
R2	0.972	0.959	0.968		0.997	0.901	0.931		0.850	0.967	0.966
L1 3YEARAVGGREENRATIOEP PUBLIC	0.158	0.826**	0.145	−1.000	−0.312	0.364*	−0.744	11.009*	0.002	0.235	0.353
	(0.351)	(0.356)	(0.251)	(1.407)	(2.757)	(0.200)	(0.565)	(6.337)	(0.004)	(0.209)	(0.233)
L1 3YEARAVGGREENRATIOEP	−0.174	0.108	−0.045	1.008	1.225	0.358**	0.900	−6.416	0.003	−0.378	−0.177
PRIVATE	(0.456)	(0.459)	(0.391)	(0.876)	(1.371)	(0.162)	(0.666)	(4.506)	(0.004)	(0.436)	(0.395)
Observations	868	868	868	239	868	868	868	239	868	868	868
R2	0.944	0.924	0.942	0.974	0.981	0.740	0.622	0.961	0.768	0.936	0.939
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: BROWNEFFRATIOEP on all firms											
L1 BROWNEFFRATIOEP PUBLIC	−0.230	−0.056	−0.064	1.704	5.613	0.033	0.582	59.264	0.000	0.004	−0.122
	(0.280)	(0.379)	(0.214)	(2.557)	(4.630)	(0.242)	(0.461)	(53.420)	(0.001)	(0.139)	(0.176)
L1 BROWNEFFRATIOEP PRIVATE	−0.117	−0.486	−0.134	−0.039	0.961	−0.288	−0.164	10.508	0.000	0.025	−0.014
	(0.171)	(0.403)	(0.099)	(0.888)	(1.402)	(0.214)	(0.334)	(11.422)	(0.001)	(0.054)	(0.076)
Observations	840	840	840	227	840	840	840	227	840	840	840
R2	0.963	0.929	0.960	0.962	0.989	0.735	0.981	0.855	0.907	0.926	0.936
L3 BROWNEFFRATIOEP PUBLIC	−0.088	0.047	−0.076	−0.712	8.016**	0.219	0.611*	49.857	0.001	−0.042	−0.156
	(0.255)	(0.223)	(0.158)	(6.787)	(3.353)	(0.299)	(0.318)	(58.322)	(0.001)	(0.097)	(0.138)
L3 BROWNEFFRATIOEP PRIVATE	−0.047	−0.347	−0.117	−0.496	−0.091	−0.378*	−0.114	−11.268	−0.001*	−0.039	0.003
	(0.218)	(0.264)	(0.084)	(1.904)	(1.323)	(0.228)	(0.196)	(15.570)	(0.001)	(0.045)	(0.073)
Observations	720	720	720	106	720	720	720	106	720	720	720
R2	0.981	0.977	0.990	0.990	0.995	0.784	0.990	0.974	0.958	0.985	0.986
L5 BROWNEFFRATIOEP PUBLIC	0.251	0.097	−0.091		3.174	0.105	0.086		0.001	0.048	−0.040
	(0.228)	(0.172)	(0.124)		(2.923)	(0.303)	(0.238)		(0.001)	(0.113)	(0.129)
L5 BROWNEFFRATIOEP PRIVATE	−0.061	−0.250	−0.092		−1.364	−0.256	−0.070		−0.001	−0.049	−0.011
	(0.228)	(0.214)	(0.060)		(1.131)	(0.190)	(0.100)		(0.000)	(0.046)	(0.063)
Observations	606	606	606		606	606	606		606	606	606
R2	0.985	0.984	0.992		0.998	0.852	0.994		0.967	0.985	0.987
L1 3YEARAVGBROWNEFFRATIOEP	0.116	−0.406	−0.011	8.975**	21.718***	0.588*	0.429	175.171	0.002	0.215	0.079
PUBLIC	(0.435)	(0.601)	(0.327)	(3.932)	(7.720)	(0.310)	(0.547)	(117.147)	(0.002)	(0.311)	(0.318)
L1 3YEARAVGBROWNEFFRATIOEP	0.034	−0.860	−0.217	−0.387	−3.414	−0.959*	−0.384	13.308	−0.003*	0.036	0.062
PRIVATE	(0.357)	(0.739)	(0.212)	(1.276)	(3.509)	(0.522)	(0.599)	(19.277)	(0.002)	(0.146)	(0.197)
Observations	874	874	874	239	874	874	874	239	874	874	874
R2	0.961	0.925	0.958	0.968	0.989	0.735	0.978	0.872	0.896	0.911	0.933
Panel B.2: BROWNEFFRATIOEP on ever patenting firms											
L1 BROWNEFFRATIOEP PUBLIC	−0.042	−0.194	−0.383	0.674	8.296	0.058	0.303	109.525	0.002**	0.052	−0.466*
	(0.342)	(0.493)	(0.240)	(3.697)	(5.557)	(0.290)	(0.339)	(88.308)	(0.001)	(0.153)	(0.246)
L1 BROWNEFFRATIOEP PRIVATE	−0.175	−0.502	−0.144	0.511	4.056	−0.126	−0.018	18.028	−0.001	0.069	−0.097
	(0.202)	(0.482)	(0.121)	(0.903)	(2.992)	(0.307)	(0.163)	(18.012)	(0.001)	(0.054)	(0.103)
Observations	838	838	838	227	838	838	838	227	838	838	838
R2	0.962	0.960	0.985	0.957	0.928	0.682	0.977	0.728	0.948	0.981	0.982
L3 BROWNEFFRATIOEP PUBLIC	0.324	0.200	−0.028	−1.611	9.439*	0.107	0.538**	60.093	0.001	0.149	−0.309
	(0.501)	(0.367)	(0.280)	(7.674)	(5.578)	(0.359)	(0.239)	(75.092)	(0.001)	(0.148)	(0.268)
L3 BROWNEFFRATIOEP PRIVATE	−0.160	−0.419	−0.120	−0.160	3.084	−0.217	−0.083	−9.388	−0.001	0.084	−0.004
	(0.233)	(0.435)	(0.105)	(1.695)	(2.451)	(0.299)	(0.117)	(17.022)	(0.001)	(0.071)	(0.101)
Observations	717	717	717	106	717	717	717	106	717	717	717
R2	0.974	0.972	0.989	0.988	0.954	0.740	0.988	0.938	0.965	0.984	0.986
L5 BROWNEFFRATIOEP PUBLIC	0.504	0.139	−0.116		−1.333	0.084	0.056		0.001	0.158	−0.168
	(0.449)	(0.307)	(0.196)		(5.360)	(0.322)	(0.199)		(0.001)	(0.122)	(0.219)
L5 BROWNEFFRATIOEP PRIVATE	0.298	−0.275	0.084		1.538	−0.295	−0.008		−0.001**	0.033	0.105
	(0.269)	(0.334)	(0.131)		(1.693)	(0.223)	(0.092)		(0.001)	(0.079)	(0.122)
Observations	605	605	605		605	605	605		605	605	605
R2	0.981	0.981	0.992		0.969	0.823	0.993		0.977	0.987	0.989
L1 3YEARAVGBROWNEFFRATIOEP	0.219	−1.643	−0.242	11.232*	46.438**	0.618*	1.343**	314.088	0.002	0.275	−0.636
PUBLIC	(0.650)	(1.094)	(0.382)	(5.872)	(18.424)	(0.341)	(0.535)	(200.823)	(0.002)	(0.196)	(0.398)
L1 3YEARAVGBROWNEFFRATIOEP	−0.249	−1.173	−0.327	2.156	5.363	−0.791	−0.180	42.598	−0.001	0.270*	−0.109
PRIVATE	(0.473)	(0.762)	(0.267)	(1.581)	(5.332)	(0.675)	(0.382)	(35.265)	(0.001)	(0.160)	(0.247)
Observations	871	871	871	237	871	871	871	237	871	871	871
R2	0.961	0.958	0.985	0.957	0.915	0.681	0.976	0.769	0.947	0.980	0.982
Panel B.3: BROWNEFFRATIOEP on never patenting firms											
L1 BROWNEFFRATIOEP PUBLIC	−0.102	0.242	0.298	−0.648	1.209	−0.134	0.376	−9.431	−0.006	0.228	0.387*
	(0.428)	(0.370)	(0.286)	(1.839)	(3.517)	(0.214)	(0.501)	(9.587)	(0.004)	(0.200)	(0.228)
L1 BROWNEFFRATIOEP PRIVATE	−0.280	−0.723	−0.196	−0.119	0.376	−0.247	−0.368	2.395	−0.002	−0.131	−0.080
	(0.199)	(0.553)	(0.160)	(0.917)	(1.061)	(0.169)	(0.373)	(4.799)	(0.002)	(0.119)	(0.141)
Observations	834	834	834	227	834	834	834	227	834	834	834
R2	0.948	0.928	0.945	0.974	0.990	0.753	0.959	0.961	0.765	0.944	0.940
L3 BROWNEFFRATIOEP PUBLIC	−0.156	0.063	−0.029	−1.433	3.463	0.125	−0.144	8.824	−0.001	0.214	0.234
	(0.380)	(0.283)	(0.254)	(1.865)	(2.437)	(0.206)	(0.501)	(11.134)	(0.005)	(0.180)	(0.199)
L3 BROWNEFFRATIOEP PRIVATE	−0.016	−0.218	−0.036	−0.143	−1.021	−0.336**	−0.225	−10.388	−0.001	−0.050	0.046
	(0.190)	(0.175)	(0.126)	(0.893)	(0.804)	(0.146)	(0.192)	(9.316)	(0.002)	(0.118)	(0.127)
Observations	710	710	710	106	710	710	710	106	710	710	710
R2	0.961	0.950	0.963	0.998	0.994	0.850	0.859	0.996	0.799	0.960	0.960
L5 BROWNEFFRATIOEP PUBLIC	0.015	0.130	−0.128		2.888	−0.032	−0.137		0.003	0.179	0.121
	(0.310)	(0.280)	(0.246)		(1.973)	(0.178)	(0.382)		(0.004)	(0.182)	(0.227)
L5 BROWNEFFRATIOEP PRIVATE	−0.013	−0.045	−0.074		−2.174**	−0.172	−0.150		0.000	−0.014	0.018
	(0.198)	(0.140)	(0.130)		(1.018)	(0.106)	(0.121)		(0.002)	(0.135)	(0.131)
Observations	594	594	594		594	594	594		594	594	594
R2	0.972	0.959	0.968		0.997	0.900	0.931		0.849	0.967	0.966
L1 3YEARAVGBROWNEFFRATIOEP	0.183	−0.007	0.210	2.360	11.620**	0.212	−1.169	−3.051	−0.003	0.440	0.628*
PUBLIC	(0.556)	(0.570)	(0.379)	(2.706)	(5.737)	(0.297)	(1.213)	(14.858)	(0.006)	(0.346)	(0.342)
L1 3YEARAVGBROWNEFFRATIOEP	−0.374	−1.190	−0.114	−0.951	−3.922	−0.811**	−0.988	−6.532	−0.002	−0.172	0.071
PRIVATE	(0.401)	(0.948)	(0.265)	(1.399)	(2.494)	(0.376)	(0.773)	(8.570)	(0.004)	(0.194)	(0.219)
Observations	868	868	868	239	868	868	868	239	868	868	868
R2	0.944	0.924	0.942	0.974	0.981	0.740	0.621	0.960	0.768	0.936	0.939
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.12. Public and Private Patent Ratios and Cross-Industry Outcomes

The unit of observation is GICS-8 industry-year. The sample period is 2005 to 2020. We aggregate the dependent variables at a given GICS-8 industry's higher GICS-2 level including all GICS-8 industries but the given GICS-8 industry used for the independent variables. The dependent variables are thus GICS-2 industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively GICS-2 industry level cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years for the Trucost sample. In Panel A.1 and B1., dependent variables are calculated across all firms in the broader GICS-2 industry except the given GICS-8 industry. In Panel A.2 and B.2, dependent variables are similarly calculated only for ever-patenting firms and in Panel A.3 and B.3 only for never-patenting firms. In Panel A, the key independent variables of interest are the GICS-8 industry level GREENRATIOEP PUBLIC and GREENRATIOEP PRIVATE and in Panel B the GICS-8 industry level BROWNEFFRATIOEP PUBLIC and BROWNEFFRATIOEP PRIVATE. Controls at the GICS-8 all firms (ever-patenting, respectively never patenting) level include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI.* Independent variables are either GICS-8 industry level logs of sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-8 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: GREENRATIOEP on all firms											
L1 GREENRATIOEP PUBLIC/100	8.280*	7.327	2.349	23.432	−16.982	5.085	−6.320	233.107	−0.008	0.047	1.980
	(4.460)	(6.824)	(5.165)	(21.464)	(26.596)	(3.194)	(5.842)	(173.471)	(0.025)	(2.782)	(5.575)
L1 GREENRATIOEP PRIVATE/100	−1.516	4.846	−6.096**	−14.892	−5.725	2.567	−5.545	−8.574	−0.027**	−3.423**	−4.393
	(2.665)	(5.238)	(2.989)	(9.937)	(21.433)	(2.173)	(3.578)	(147.237)	(0.013)	(1.735)	(3.157)
Observations	1314	1314	1314	371	1314	1314	1314	371	1314	1314	1314
R2	0.991	0.975	0.983	0.986	0.989	0.977	0.982	0.957	0.944	0.985	0.964
L3 GREENRATIOEP PUBLIC/100	5.226	−2.191	−1.337	−9.591	−10.427	1.825	−5.960	−304.854*	−0.006	−2.184	−1.071
	(3.366)	(5.038)	(5.440)	(19.128)	(21.717)	(2.685)	(4.491)	(154.208)	(0.028)	(2.536)	(5.731)
L3 GREENRATIOEP PRIVATE/100	−1.683	−0.219	−7.841***	5.560	31.812*	2.215	−1.423	85.377	−0.018	−3.927***	−7.262**
	(1.782)	(3.731)	(2.536)	(12.359)	(18.104)	(1.696)	(3.120)	(126.479)	(0.013)	(1.390)	(2.820)
Observations	1115	1115	1115	172	1115	1115	1115	172	1115	1115	1115
R2	0.996	0.986	0.988	0.998	0.993	0.985	0.990	0.995	0.957	0.989	0.972
L5 GREENRATIOEP PUBLIC/100	3.499	−0.204	1.210	9.621	−3.798	−2.394	−0.442	9.621	−0.039	−2.856	0.999
	(3.835)	(5.103)	(5.461)	(12.575)	(18.064)	(2.454)	(3.431)	(12.575)	(0.027)	(2.335)	(5.707)
L5 GREENRATIOEP PRIVATE/100	−3.581**	−1.040	−9.376***	−14.044*	50.118***	2.427	0.602	−14.044*	−0.010	−4.152***	−9.745***
	(1.388)	(3.139)	(2.255)	(7.314)	(16.161)	(1.616)	(2.447)	(7.314)	(0.011)	(1.407)	(2.551)
Observations	926	926	926	933	926	926	926	933	926	926	926
R2	0.998	0.991	0.991	0.114	0.995	0.990	0.995	0.114	0.970	0.992	0.979
3YEARAVGGREENRATIOEP	0.064	0.097	−0.066	−0.699**	−0.665*	0.075	−0.145	−1.497	0.000	−0.037	−0.081
PUBLIC/100	(0.062)	(0.115)	(0.069)	(0.333)	(0.382)	(0.046)	(0.098)	(2.713)	(0.000)	(0.040)	(0.072)
3YEARAVGGREENRATIOEP	−0.029	−0.042	−0.156***	−0.221**	0.654**	0.020	−0.050	−4.111***	−0.000***	−0.079***	−0.134***
PRIVATE/100	(0.030)	(0.073)	(0.038)	(0.108)	(0.277)	(0.029)	(0.060)	(1.567)	(0.000)	(0.023)	(0.038)
Observations	1460	1460	1460	411	1460	1460	1460	411	1460	1460	1460
R2	0.991	0.970	0.984	0.985	0.990	0.976	0.982	0.957	0.946	0.985	0.967
Panel A.2: GREENRATIOEP on ever patenting firms											
L1 GREENRATIOEP PUBLIC/100	−6.270	3.558	−3.944	39.689	−87.309**	2.512	−13.575*	391.410	−0.004	−3.432	0.086
	(6.171)	(5.953)	(4.779)	(30.401)	(41.507)	(3.209)	(7.329)	(293.564)	(0.017)	(3.240)	(4.970)
L1 GREENRATIOEP PRIVATE/100	−2.901	5.102	−6.466**	−12.979	−36.250	1.550	−7.257*	−24.937	−0.013	−5.737***	−4.190
	(3.659)	(5.134)	(2.931)	(10.961)	(32.315)	(2.103)	(3.829)	(169.707)	(0.009)	(2.129)	(3.018)
Observations	1305	1305	1305	368	1305	1305	1305	368	1305	1305	1305
R2	0.987	0.978	0.988	0.978	0.974	0.969	0.978	0.899	0.959	0.983	0.971
L3 GREENRATIOEP PUBLIC/100	−1.652	−4.825	−5.100	−26.067	−16.046	1.513	−8.714	−485.493**	0.005	−4.854	−4.081
	(4.404)	(4.717)	(3.701)	(32.307)	(18.186)	(3.455)	(5.607)	(226.235)	(0.018)	(2.991)	(4.871)
L3 GREENRATIOEP PRIVATE/100	−0.161	2.635	−7.357***	−48.029	12.540	3.017	−1.887	−240.666	−0.009	−7.142***	−7.149**
	(2.714)	(4.787)	(2.385)	(30.278)	(21.187)	(2.008)	(3.309)	(166.204)	(0.009)	(2.084)	(2.799)
Observations	1109	1109	1109	172	1109	1109	1109	172	1109	1109	1109
R2	0.994	0.987	0.993	0.995	0.988	0.979	0.988	0.984	0.969	0.987	0.979
L5 GREENRATIOEP PUBLIC/100	−6.441	−3.603	−6.005*	31.310***	−7.484	−2.868	−3.682	31.310***	−0.016	−8.008***	−3.650
	(4.595)	(4.004)	(3.403)	(10.169)	(14.257)	(3.132)	(4.699)	(10.169)	(0.017)	(2.768)	(4.901)
L5 GREENRATIOEP PRIVATE/100	−2.107	2.707	−7.677***	4.740	11.067	3.591**	0.496	4.740	−0.008	−6.327***	−8.646***
	(2.185)	(3.659)	(2.206)	(6.465)	(16.615)	(1.800)	(2.594)	(6.465)	(0.007)	(2.005)	(2.660)
Observations	921	921	921	933	921	921	921	933	921	921	921
R2	0.997	0.993	0.995	0.127	0.994	0.985	0.993	0.127	0.980	0.991	0.985
3YEARAVGGREENRATIOEP	−0.107	0.032	−0.131*	−0.654	−1.619**	0.018	−0.227*	−3.801	0.000	−0.150***	−0.122*
PUBLIC/100	(0.089)	(0.107)	(0.074)	(0.437)	(0.663)	(0.041)	(0.117)	(3.433)	(0.000)	(0.047)	(0.066)
3YEARAVGGREENRATIOEP	−0.035	0.011	−0.158***	−0.167	0.276	0.034	−0.042	−3.756**	−0.000**	−0.127***	−0.149***
PRIVATE/100	(0.043)	(0.080)	(0.037)	(0.139)	(0.443)	(0.030)	(0.064)	(1.793)	(0.000)	(0.028)	(0.037)
Observations	1444	1444	1444	404	1444	1444	1444	404	1444	1444	1444
R2	0.987	0.972	0.989	0.977	0.971	0.968	0.977	0.898	0.961	0.984	0.973
Panel A.3: GREENRATIOEP on never patenting firms											
L1 GREENRATIOEP PUBLIC/100	35.560***	1.319	2.843	9.163	16.470	5.087	2.023	155.658	−0.055	−1.432	−1.909
	(10.555)	(10.289)	(7.291)	(18.541)	(51.179)	(5.689)	(7.630)	(148.198)	(0.085)	(5.221)	(6.417)
L1 GREENRATIOEP PRIVATE/100	−4.616	2.819	−3.943	−11.639	77.020*	2.142	−4.752	32.147	−0.036	−4.019	−1.405
	(5.444)	(8.032)	(4.695)	(9.544)	(46.782)	(3.936)	(4.902)	(170.872)	(0.046)	(3.431)	(4.561)
Observations	1273	1273	1273	371	1273	1273	1273	371	1273	1273	1273
R2	0.974	0.941	0.969	0.994	0.987	0.969	0.977	0.993	0.903	0.967	0.958
L3 GREENRATIOEP PUBLIC/100	15.651*	−5.757	0.249	6.655	−15.246	−0.301	−2.337	−85.067	−0.075	−4.572	−0.477
	(8.437)	(7.522)	(7.205)	(12.709)	(38.046)	(2.232)	(6.431)	(108.943)	(0.072)	(3.962)	(6.129)
L3 GREENRATIOEP PRIVATE/100	−2.655	−4.759	−5.924	5.620	86.288**	−0.826	−5.778	50.901	−0.072*	−4.635	−1.276
	(4.746)	(6.039)	(4.104)	(7.333)	(42.279)	(1.578)	(4.411)	(75.653)	(0.041)	(3.133)	(4.037)
Observations	1065	1065	1065	172	1065	1065	1065	172	1065	1065	1065
R2	0.985	0.957	0.977	0.999	0.992	0.990	0.985	1.000	0.939	0.974	0.966
L5 GREENRATIOEP PUBLIC/100	6.583	−9.614	0.169	12.343	20.095	−3.244*	1.678	12.343	−0.082	−7.951**	0.767
	(9.025)	(6.782)	(7.130)	(10.399)	(31.180)	(1.771)	(5.305)	(10.399)	(0.077)	(3.796)	(6.012)
L5 GREENRATIOEP PRIVATE/100	−5.349*	−5.410	−9.010**	−10.096	97.418***	−0.113	−6.898**	−10.096	−0.063*	−6.108**	−4.223
	(2.995)	(5.061)	(3.767)	(7.374)	(36.378)	(1.179)	(3.216)	(7.374)	(0.037)	(2.955)	(3.647)
Observations	872	872	872	899	872	872	872	899	872	872	872
R2	0.993	0.967	0.984	0.103	0.995	0.995	0.992	0.103	0.961	0.980	0.974
3YEARAVGGREENRATIOEP	0.342**	−0.038	−0.125	−0.790***	−0.030	0.137*	−0.043	1.059	−0.001	−0.145**	−0.144*
PUBLIC/100	(0.163)	(0.149)	(0.099)	(0.204)	(0.698)	(0.078)	(0.112)	(2.742)	(0.001)	(0.068)	(0.085)
3YEARAVGGREENRATIOEP	0.068	0.016	−0.013	−0.002	1.575**	−0.010	−0.099	−2.750	−0.001**	−0.013	0.056
PRIVATE/100	(0.082)	(0.124)	(0.065)	(0.100)	(0.616)	(0.047)	(0.074)	(1.705)	(0.001)	(0.057)	(0.068)
Observations	1416	1416	1416	411	1416	1416	1416	411	1416	1416	1416
R2	0.974	0.938	0.969	0.994	0.988	0.968	0.976	0.993	0.906	0.967	0.959
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: BROWNEFFRATIOEP on all firms											
L1 BROWNEFFRATIOEP PUBLIC/100	3.143	−5.589	4.690	7.505	−38.934	−7.519**	20.039	−40.740	−0.059	−2.297	1.827
	(7.946)	(8.013)	(6.451)	(15.392)	(38.663)	(3.423)	(12.226)	(160.160)	(0.038)	(2.940)	(6.992)
L1 BROWNEFFRATIOEP PRIVATE/100	2.876	−5.520	0.794	−26.340	−9.274	−3.897	−3.538	−35.380	−0.091***	−4.719	1.670
	(4.632)	(10.948)	(5.912)	(32.509)	(42.967)	(5.642)	(6.045)	(233.242)	(0.032)	(3.187)	(6.181)
Observations	1314	1314	1314	371	1314	1314	1314	371	1314	1314	1314
R2	0.991	0.975	0.983	0.986	0.989	0.977	0.983	0.956	0.945	0.984	0.964
L3 BROWNEFFRATIOEP PUBLIC/100	−5.693	7.075	0.776	44.946	−31.761	1.157	11.968	191.834	−0.044	−2.740	1.114
	(4.708)	(6.223)	(8.270)	(38.554)	(47.187)	(3.357)	(7.458)	(438.834)	(0.036)	(3.981)	(7.631)
L3 BROWNEFFRATIOEP PRIVATE/100	−1.945	−6.020	2.541	19.015	−67.035	−3.875	−5.271	263.626	−0.076***	−2.106	4.450
	(3.838)	(7.418)	(5.625)	(21.300)	(43.016)	(3.887)	(5.272)	(248.375)	(0.029)	(2.564)	(5.699)
Observations	1115	1115	1115	172	1115	1115	1115	172	1115	1115	1115
R2	0.996	0.986	0.988	0.998	0.993	0.985	0.990	0.994	0.958	0.989	0.972
L5 BROWNEFFRATIOEP PUBLIC/100	−1.139	8.005*	5.655	−20.372	−16.961	0.919	13.238*	−20.372	−0.011	1.879	3.785
	(3.595)	(4.650)	(5.310)	(16.097)	(35.689)	(4.274)	(7.262)	(16.097)	(0.031)	(2.748)	(5.023)
L5 BROWNEFFRATIOEP PRIVATE/100	−5.409	−3.890	−1.033	−4.332	−76.614*	−2.780	−1.532	−4.332	−0.032*	−0.011	−0.075
	(3.724)	(5.267)	(5.155)	(13.816)	(39.504)	(2.841)	(4.727)	(13.816)	(0.018)	(2.234)	(4.681)
Observations	926	926	926	933	926	926	926	933	926	926	926
R2	0.998	0.991	0.991	0.110	0.995	0.990	0.995	0.110	0.970	0.992	0.979
3YEARAVGBROWNEFFRATIOEP	−0.087	0.392***	0.084	−0.092	−0.715	0.028	−0.117	−5.446	−0.001*	0.073	0.173
PUBLIC/100	(0.110)	(0.151)	(0.122)	(0.650)	(0.691)	(0.083)	(0.197)	(9.787)	(0.001)	(0.090)	(0.133)
3YEARAVGBROWNEFFRATIOEP	−0.109	0.188	−0.006	−0.927**	−1.670**	−0.004	−0.150	−11.113**	−0.001***	−0.064	0.024
PRIVATE/100	(0.090)	(0.191)	(0.073)	(0.423)	(0.672)	(0.101)	(0.113)	(4.908)	(0.000)	(0.039)	(0.072)
Observations	1460	1460	1460	411	1460	1460	1460	411	1460	1460	1460
R2	0.991	0.970	0.984	0.985	0.990	0.976	0.982	0.957	0.946	0.985	0.967
Panel B.2: BROWNEFFRATIOEP on ever patenting firms											
L1 BROWNEFFRATIOEP PUBLIC/100	−5.973	−4.313	0.376	16.137	23.796	−6.508	15.818	105.936	−0.042**	−4.507	0.065
	(5.953)	(8.817)	(6.187)	(19.963)	(38.027)	(4.281)	(10.843)	(241.195)	(0.016)	(4.997)	(6.097)
L1 BROWNEFFRATIOEP PRIVATE/100	6.599	−9.218	−1.627	−27.443	5.726	−5.214	−5.865	−44.855	−0.037*	−4.767	−0.542
	(6.259)	(10.445)	(5.907)	(38.540)	(57.902)	(5.261)	(6.617)	(351.823)	(0.022)	(4.954)	(6.371)
Observations	1305	1305	1305	368	1305	1305	1305	368	1305	1305	1305
R2	0.987	0.978	0.988	0.978	0.973	0.969	0.978	0.898	0.959	0.983	0.971
L3 BROWNEFFRATIOEP PUBLIC/100	−12.441**	4.769	−2.352	78.701	−28.108	−1.031	10.614	377.226	−0.000	−1.423	−0.639
	(5.717)	(7.114)	(8.423)	(61.368)	(31.632)	(3.866)	(8.531)	(583.709)	(0.017)	(6.999)	(7.650)
L3 BROWNEFFRATIOEP PRIVATE/100	4.150	−6.583	0.624	60.649	28.185	−2.953	−4.866	644.377**	−0.030	−2.244	1.665
	(5.283)	(9.304)	(4.872)	(65.568)	(38.182)	(4.657)	(4.949)	(306.466)	(0.020)	(4.221)	(5.625)
Observations	1109	1109	1109	172	1109	1109	1109	172	1109	1109	1109
R2	0.994	0.987	0.992	0.995	0.988	0.978	0.988	0.985	0.970	0.987	0.979
L5 BROWNEFFRATIOEP PUBLIC/100	−5.808	6.139	1.654	−1.869	−20.527	0.707	9.848	−1.869	0.010	4.010	2.459
	(4.242)	(4.924)	(5.964)	(16.689)	(25.111)	(5.014)	(8.304)	(16.689)	(0.018)	(4.617)	(5.616)
L5 BROWNEFFRATIOEP PRIVATE/100	−1.059	−5.127	0.047	−0.171	15.585	−3.237	−0.711	−0.171	−0.014	2.361	0.481
	(4.991)	(6.570)	(5.065)	(13.806)	(36.925)	(3.723)	(4.499)	(13.806)	(0.013)	(3.698)	(4.816)
Observations	921	921	921	933	921	921	921	933	921	921	921
R2	0.997	0.993	0.995	0.118	0.994	0.985	0.993	0.118	0.980	0.991	0.984
3YEARAVGBROWNEFFRATIOEP	−0.358**	0.346**	−0.065	−0.318	−1.208	0.050	−0.239	−7.885	−0.000	−0.071	0.097
PUBLIC/100	(0.143)	(0.173)	(0.130)	(0.775)	(0.919)	(0.083)	(0.202)	(11.797)	(0.000)	(0.107)	(0.140)
3YEARAVGBROWNEFFRATIOEP	−0.085	0.129	−0.051	−0.926*	−1.398	−0.031	−0.242**	−10.925*	−0.001**	−0.116**	−0.003
PRIVATE/100	(0.115)	(0.196)	(0.077)	(0.525)	(0.939)	(0.101)	(0.116)	(5.680)	(0.000)	(0.054)	(0.073)
Observations	1444	1444	1444	404	1444	1444	1444	404	1444	1444	1444
R2	0.987	0.972	0.988	0.977	0.971	0.968	0.977	0.898	0.961	0.983	0.972
Panel B.3: BROWNEFFRATIOEP on never patenting firms											
L1 BROWNEFFRATIOEP PUBLIC/100	12.652	−2.111	20.617**	−19.545	−118.973	−10.287*	39.007**	−139.761	−0.104	5.824	9.584
	(20.442)	(14.917)	(9.201)	(12.455)	(91.657)	(5.527)	(18.152)	(128.509)	(0.110)	(5.926)	(10.238)
L1 BROWNEFFRATIOEP PRIVATE/100	−8.080	−3.510	−1.246	−5.726	−26.377	3.235	−3.479	−30.901	−0.237***	−8.896	−0.085
	(11.207)	(13.500)	(8.809)	(18.924)	(120.042)	(8.217)	(7.992)	(158.910)	(0.080)	(6.496)	(7.969)
Observations	1273	1273	1273	371	1273	1273	1273	371	1273	1273	1273
R2	0.973	0.941	0.969	0.994	0.987	0.969	0.977	0.993	0.903	0.967	0.958
L3 BROWNEFFRATIOEP PUBLIC/100	2.472	18.274	11.709	−3.784	−122.015	5.115	19.047*	30.574	−0.160	0.330	7.489
	(16.331)	(14.505)	(11.715)	(17.275)	(88.459)	(4.268)	(11.300)	(234.285)	(0.099)	(7.050)	(10.180)
L3 BROWNEFFRATIOEP PRIVATE/100	−12.779	−0.858	5.306	14.336	−219.660*	−3.741	−7.411	9.582	−0.170**	−0.163	8.324
	(9.820)	(9.069)	(7.818)	(9.087)	(112.214)	(3.786)	(10.121)	(66.457)	(0.067)	(5.520)	(6.713)
Observations	1065	1065	1065	172	1065	1065	1065	172	1065	1065	1065
R2	0.985	0.957	0.977	0.999	0.992	0.990	0.985	1.000	0.939	0.974	0.966
L5 BROWNEFFRATIOEP PUBLIC/100	−8.601	8.703	10.664	−2.721	−87.553	0.533	15.106*	−2.721	−0.118	−0.677	5.337
	(13.621)	(10.220)	(8.099)	(17.038)	(68.480)	(3.521)	(8.936)	(17.038)	(0.086)	(5.297)	(7.212)
L5 BROWNEFFRATIOEP PRIVATE/100	−9.812	15.756**	5.592	18.900	−222.718**	2.056	−2.440	18.900	−0.059	5.602	5.809
	(7.374)	(7.931)	(7.105)	(12.819)	(107.149)	(2.508)	(8.593)	(12.819)	(0.071)	(4.624)	(5.972)
Observations	872	872	872	899	872	872	872	899	872	872	872
R2	0.993	0.967	0.984	0.102	0.995	0.995	0.992	0.102	0.961	0.980	0.974
3YEARAVGBROWNEFFRATIOEP	0.201	0.277	0.273	−0.466	−0.869	−0.019	0.193	−4.757	−0.003	0.189	0.218
PUBLIC/100	(0.273)	(0.252)	(0.184)	(0.443)	(1.379)	(0.130)	(0.216)	(8.060)	(0.002)	(0.133)	(0.172)
3YEARAVGBROWNEFFRATIOEP	−0.204	0.078	−0.102	−0.443	−2.001	0.090	−0.158	−11.054**	−0.002	−0.095	−0.069
PRIVATE/100	(0.185)	(0.237)	(0.122)	(0.276)	(1.752)	(0.139)	(0.152)	(4.943)	(0.001)	(0.094)	(0.116)
Observations	1416	1416	1416	411	1416	1416	1416	411	1416	1416	1416
R2	0.974	0.938	0.969	0.994	0.988	0.968	0.976	0.993	0.906	0.967	0.959
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.16. Patent Ratios Explanatory Power

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT and S123UPTOT over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT and S3DOWNINT for 1, 3 or 5 years. The key independent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 year in Panel A. In Panel B, the key independent variable is similarly defined for *BROWNEFFRATIOEP*. The ratios are defined in Table 3.2. Controls include: *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET* and *MSCI*. All variables are similarly lagged by 1, 3, or 5 years and defined in Table 3.1. The model is estimated using pooled regression model. All regressions include country and year fixed effects. We report the partial R2 for the key independent variable GREENRATIOEP or BROWNEFFRATIOEP. We also report the R2 for the full model and the reduced model with all fixed effects and controls except for the patent ratio variable. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

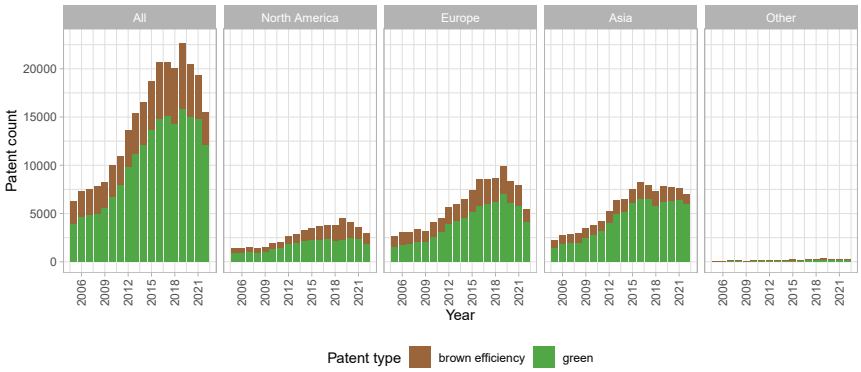
	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT
Panel A: Green innovation									
L1 GREENRATIOEP	0.514***	−0.199***	−0.059**	0.153	0.111***	1.385***	0.042***	0.146***	4.168***
	(0.041)	(0.033)	(0.029)	(0.097)	(0.028)	(0.128)	(0.013)	(0.036)	(0.610)
Partial R2	0.00596	0.00167	0.000172	0.000219	0.000628	0.00760	0.000378	0.000552	0.00579
R2 Full Model	0.668	0.742	0.785	0.459	0.810	0.149	0.171	0.226	0.106
R2 Reduced Model	0.666	0.742	0.785	0.459	0.809	0.143	0.171	0.225	0.101
Observations	31049	31049	31048	11600	31049	31049	31049	31049	11600
L3 GREENRATIOEP	0.592***	−0.199***	−0.022	0.172	0.172***	1.553***	0.040**	0.145***	4.720***
	(0.048)	(0.039)	(0.034)	(0.145)	(0.032)	(0.157)	(0.016)	(0.043)	(0.956)
Partial R2	0.00748	0.00163	0.0000243	0.000293	0.00151	0.00868	0.000320	0.000518	0.00712
R2 Full Model	0.659	0.731	0.765	0.493	0.795	0.159	0.187	0.218	0.113
R2 Reduced Model	0.656	0.730	0.765	0.493	0.795	0.152	0.186	0.217	0.106
Observations	23485	23485	23485	5419	23485	23485	23485	23485	5428
L5 GREENRATIOEP	0.695***	−0.253***	0.017		0.234***	1.789***	0.009	0.146***	
	(0.060)	(0.048)	(0.040)		(0.039)	(0.200)	(0.019)	(0.054)	
Partial R2	0.00954	0.00251	0.0000144		0.00270	0.0100	0.0000167	0.000484	
R2 Full Model	0.635	0.701	0.730		0.768	0.168	0.196	0.209	
R2 Reduced Model	0.631	0.700	0.730		0.767	0.159	0.196	0.209	
Observations	16892	16892	16892		16892	16892	16892	16892	
L1 3YEARAVGGREENRATIOEP	0.552***	−0.226***	−0.069**	0.239***	0.129***	1.561***	0.057***	0.185***	5.290***
	(0.038)	(0.032)	(0.027)	(0.091)	(0.027)	(0.126)	(0.013)	(0.035)	(0.603)
Partial R2	0.00620	0.00192	0.000205	0.000480	0.000748	0.00836	0.000626	0.000793	0.00808
R2 Full Model	0.670	0.740	0.782	0.460	0.807	0.150	0.168	0.214	0.111
R2 Reduced Model	0.668	0.739	0.782	0.460	0.807	0.143	0.167	0.213	0.104
Observations	38934	38934	38933	15245	38934	38934	38934	38934	15245
Panel B: Brown efficiency innovation									
L1 BROWNEFFRATIOEP	0.511***	−0.374***	0.578***	1.656***	0.584***	1.604***	−0.210***	0.637***	9.014***
	(0.071)	(0.062)	(0.047)	(0.193)	(0.043)	(0.287)	(0.021)	(0.064)	(1.383)
Partial R2	0.00185	0.00185	0.00519	0.00709	0.00548	0.00320	0.00294	0.00331	0.00744
R2 Full Model	0.667	0.742	0.786	0.463	0.811	0.146	0.173	0.228	0.108
R2 Reduced Model	0.666	0.742	0.785	0.459	0.809	0.143	0.171	0.225	0.101
Observations	31049	31049	31048	11600	31049	31049	31049	31049	11600
L3 BROWNEFFRATIOEP	0.531***	−0.474***	0.571***	1.613***	0.597***	2.030***	−0.229***	0.626***	8.168***
	(0.085)	(0.072)	(0.056)	(0.259)	(0.052)	(0.352)	(0.025)	(0.073)	(1.969)
Partial R2	0.00201	0.00309	0.00534	0.00714	0.00606	0.00494	0.00354	0.00322	0.00588
R2 Full Model	0.657	0.731	0.766	0.497	0.796	0.156	0.189	0.220	0.111
R2 Reduced Model	0.656	0.730	0.765	0.493	0.795	0.152	0.186	0.217	0.106
Observations	23485	23485	23485	5419	23485	23485	23485	23485	5428
L5 BROWNEFFRATIOEP	0.584***	−0.576***	0.589***		0.629***	2.338***	−0.273***	0.659***	
	(0.102)	(0.084)	(0.064)		(0.062)	(0.426)	(0.029)	(0.086)	
Partial R2	0.00245	0.00474	0.00599		0.00705	0.00620	0.00504	0.00359	
R2 Full Model	0.632	0.701	0.732		0.769	0.165	0.200	0.211	
R2 Reduced Model	0.631	0.700	0.730		0.767	0.159	0.196	0.209	
Observations	16892	16892	16892		16892	16892	16892	16892	
L1 3YEARAVGBROWNEFFRATIOEP	0.587***	−0.488***	0.599***	1.528***	0.622***	2.065***	−0.215***	0.720***	8.439***
	(0.068)	(0.060)	(0.045)	(0.176)	(0.042)	(0.283)	(0.021)	(0.060)	(1.279)
Partial R2	0.00212	0.00270	0.00469	0.00575	0.00521	0.00442	0.00274	0.00362	0.00603
R2 Full Model	0.669	0.740	0.783	0.463	0.808	0.146	0.169	0.216	0.109
R2 Reduced Model	0.668	0.739	0.782	0.460	0.807	0.143	0.167	0.213	0.104
Observations	38934	38934	38933	15245	38934	38934	38934	38934	15245
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes

3.8 Figures

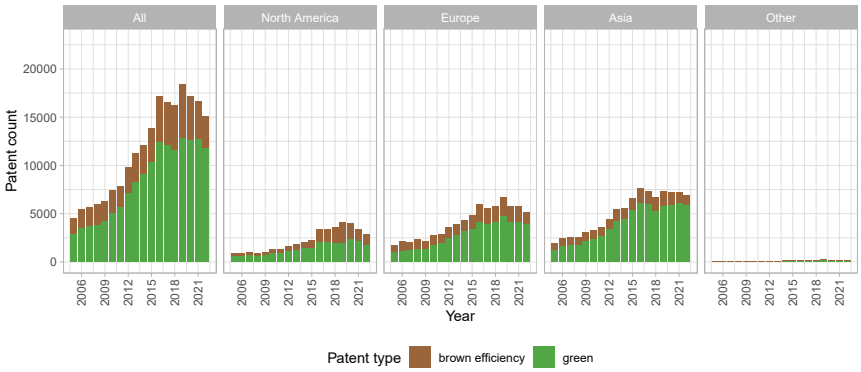
Figure 3.1. Green and Brown Efficiency EPO Patent Counts Across Regions

The sample period is 2005 to 2020. We report the total number of granted or purchased green and brown efficiency EPO patents across all regions and by region, namely North America, Europe, Asia, and other (rest of the world), per year. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.

(a) Full (public/private) sample



(b) Trucost sample



(c) Trucost (pre 2016) legacy sample

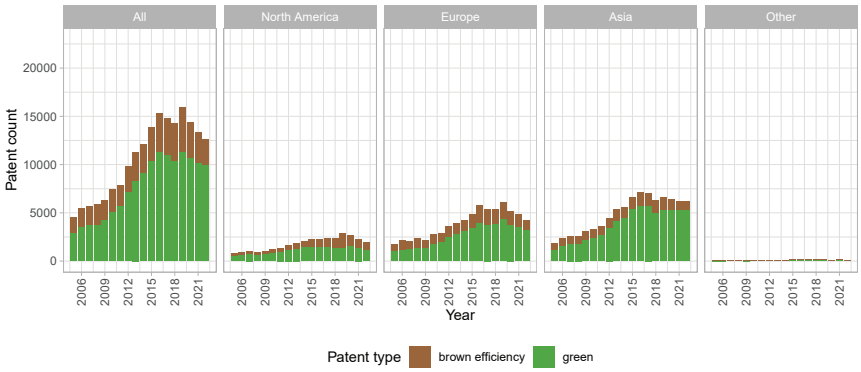


Figure 3.2. Emission reductions by technology readiness (IEA, 2020)

The figure is sourced from (IEA, 2020) and reports global energy sector CO2 emissions reductions by current technology readiness category in the Sustainable Development Scenario relative to the Stated Policies Scenario, 2019-2070. Percentages refer to cumulative emissions reductions by 2070 between the Sustainable Development Scenario and the Stated Policies Scenario enabled by technologies at a given level of maturity.

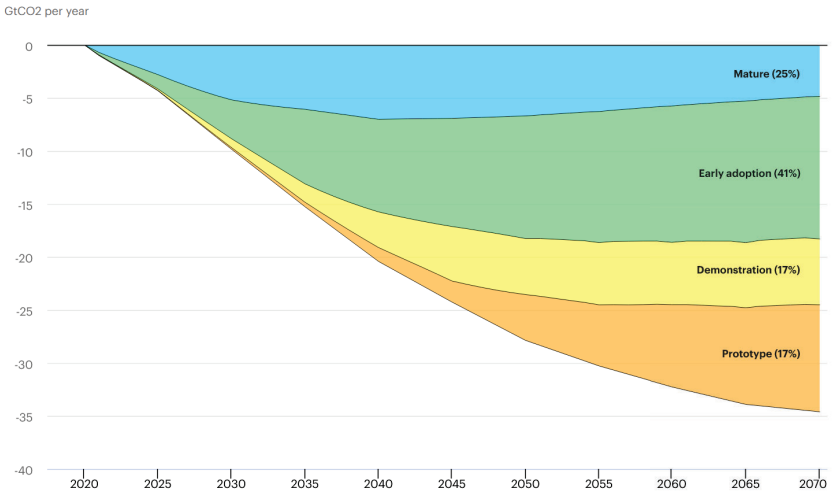


Figure 3.3. Comparing green and OECD titles

The sample is all patents granted by the European Patent Office from 2005 to 2020 that belong to the Trucost sample. Wordclouds display the top 100 words (unigrams) based on the TF-IDF comparing patent titles of GREEN patents to OECD env-tech patents, respectively OECD env-tech to GREEN patents.

(a) "Green" against "OECD"

(b) "OECD" against "Green"

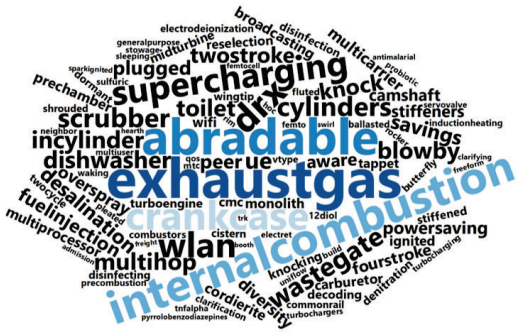
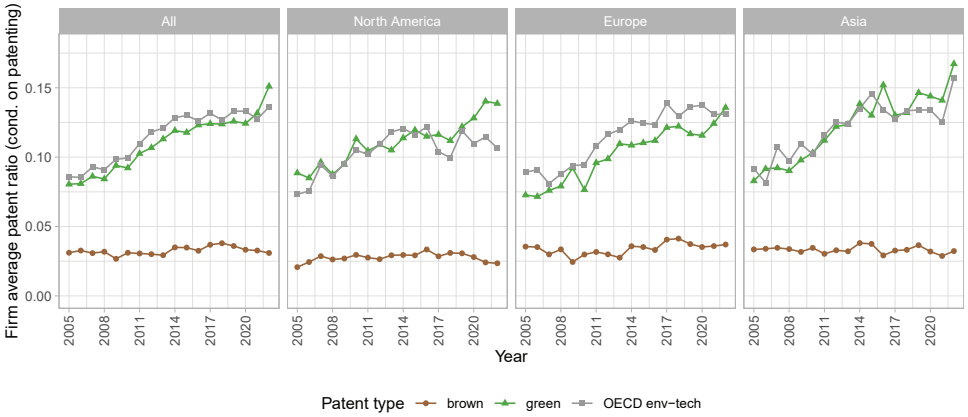


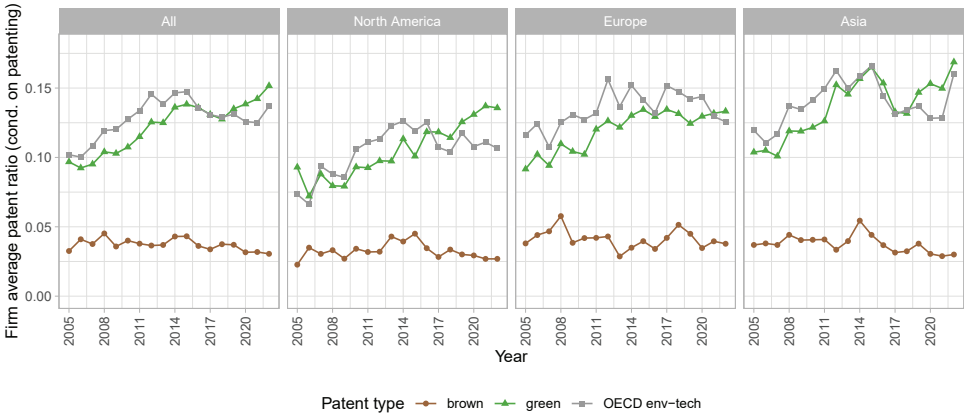
Figure 3.4. Green and Brown Efficiency EPO Patent Ratios Across Regions

The sample period is 2005 to 2020. We report the average GREENRATIOEP, BROWNEFFRATIOEP and OECDRATIOEP across all regions and for the regions North America, Europe and Asia per year. Patent ratios are defined in Table 3.2. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.

(a) Full (public/private) sample



(b) Trucost sample



(c) Trucost (pre 2016) legacy sample

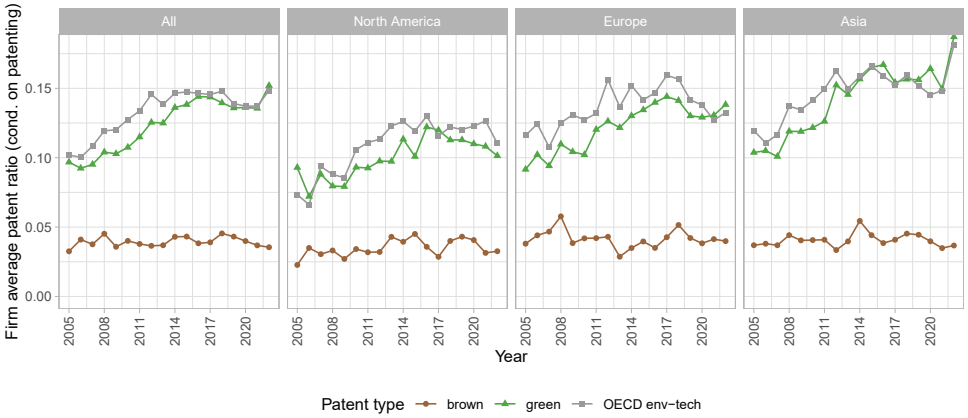
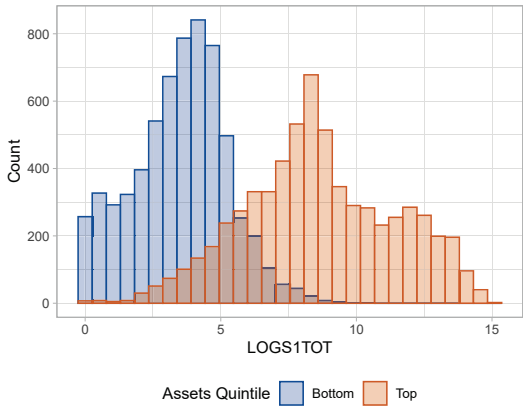


Figure 3.5. Emission distribution for different quintiles

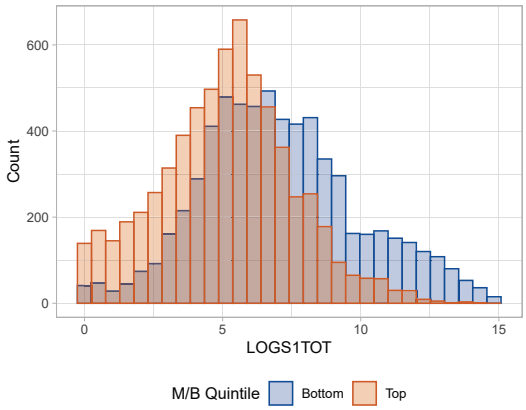
The sample period is 2005 to 2020. We report histograms for LOGS1TOT for unconditional top and bottom quintiles based on "AGE" in Panel A, "ASSETS" in Panel B, and "M/B" in Panel C. All variables are defined in Table 3.1 and 3.2.

(a) Panel A: Age quintiles

(b) Panel B: Asset quintiles



(c) Panel C: M/B quintiles



Chapter 4

Opioid Crisis and Real Estate Prices

With Cláudia Custódio and Dragana Cvijanović[1]

4.1 Introduction

Opioid usage in the United States has surged over the past two decades, resulting in nearly 500,000 deaths from opioid-related overdoses between 1999 and 2019, according to the Centers for Disease Control and Prevention.[2] The National Institute on Drug Abuse estimates that in 2017 alone, 1.7 million Americans suffered from substance use disorders related to prescription opioid pain relievers, with documented public health and economic consequences.[3] While the existing literature has mainly focused on analyzing the role of economic conditions in the bulging opioid crisis and "deaths of despair" (Case and Deaton, 2015; Finkelstein, Gentzkow, Li, and Williams, 2022), fewer studies have examined the impact of the opioid crisis on the real economy (Ouimet, Simintzi, and Ye, 2021; Harris, Kessler, Murray, and Glenn, 2019; Cornaggia, Hund, Nguyen, and Ye, 2022). We contribute to the understanding of this problem by estimating the impact of opioid abuse on real estate values.

Opioid abuse has been linked to human capital loss and direct costs to families, es-

[1] This chapter is adapted from the co-authored working paper "Opioid Crisis and Real Estate Prices", for which I was jointly responsible for the design, data collection, data analysis, and writing up.

[2] https://www.cdc.gov/drugoverdose/epidemic/index.html

[3] https://www.drugabuse.gov/drug-topics/opioids/opioid-overdose-crisis

pecially among non-college educated population (Harris, Kessler, Murray, and Glenn, 2019; Alpert, Evans, Lieber, and Powell, 2021). Prolonged opioid use can result in reduced labor productivity, leading to lower household income and job loss. As a result, families may be unable to invest in their homes or meet mortgage payments, resulting in an increase in mortgage delinquencies and the number of vacant properties. This can ultimately affect the quality and value of homes in the area. Additionally, opioid abuse can lower the attractiveness of the area by reducing residents' investments in their properties, or through residential sorting (Ahern and Giacolleti, 2022).

Understanding the impact of opioid usage on home values is important because these can act as an indicator of the local economic situation and outlook. Moreover, for a significant number of households, houses are the most valuable asset on their balance sheet (Favilukis, Ludvigson, and Van Nieuwerburgh, 2017). Rising home equity has been shown to help alleviate financing frictions and access to credit (Mian and Sufi, 2011; DeFusco, 2018), and housing collateral has been documented to spur entrepreneurship, new businesses and job creation, as it gives home owners a pledgeable asset that can be used for securing credit (Jensen, Leth-Petersen, and Nanda, 2022; Adelino, Schoar, and Severino, 2015).

To estimate the sensitivity of home values to the usage of prescription opioids we measure home values at the county level using the Zillow Home Value Index (ZHVI), and we use historic opioid prescriptions at the county level reported by the CDC between 2006 and 2018. We start by documenting a negative correlation between home values and opioid prescription rates in the short run and over a 5-year horizon. To do so, we exploit within county (over time) variation, as well as within state-year variation. Using within county variation, we estimate that a one standard deviation increase in dispensed opioid prescriptions per 100 people is associated with an up to 1.35 percentage points cumulative decrease in home values over the following 5 years. Considering that the average home value in our sample is $140,034, this translates into a $1,890 decrease in housing wealth using the within county estimates.[4]

[4]As a reference point, in 2018, 40% of Americans were not able to cover a $400 emergency with cash,

Since 2016, and in response to the opioid crisis, several US states passed laws and regulations limiting opioid prescriptions by physicians to address prescription drug misuse, abuse and overdoses. These laws generally aim to restrict duration or total dosage, in particular for first-time prescriptions, to prevent overly generous prescription and thus reduce addiction and long-term opioid usage.[5] The staggered adoption of regulation by different states arguably induces exogenous variation in prescriptions, as most evidence suggests these are driven by supply (Finkelstein, Gentzkow, Li, and Williams, 2022) and not as much by demand for opioids (Currie, Jin, and Schnell, 2019; Paulozzi, Mack, and Hockenberry, 2014).[6] We implement a difference-in-differences empirical test, in which we compare the changes in home values in years before and after the passage of the law (*the treatment*) in *treated* versus *control* counties. We first establish that the passage of these laws indeed reduced opioid prescriptions. Although we also find an increase in overdose death rates after the passage of these laws, possibly due to an increase in usage of illicit drugs in the short run, we establish that the growth in overdose death rates declines as well. This suggests that the regulation effect is likely to operate at the extensive margin of consumption of prescription drugs preventing opioid abuse in the first place. Then, we show that house values in *treated* counties increased on average upon the adoption of these regulations. We document that house values increased by 0.42 percentage points more in the year of the passage of the law, 0.81 percentage points more in the first year, and 1.78 percentage points more in the second year after the passage of the law.

To address the concern in staggered difference-in-differences estimates that already treated units act as control for units that are treated at a later stage (Sun and Abraham, 2021a; Callaway and Sant'Anna, 2021), we use interaction weighted estimates by Sun

savings or a credit-card charge that they could quickly pay off. https://www.federalreserve.gov/publications/files/2018-report-economic-well-being-us-households-201905.pdf

[5] Nevertheless, there may be unintended consequences of these laws. Patients that are unable to access medical opioids may turn to heroin or other illicit drugs as last resort to reduce their pain.

[6] Ouimet, Simintzi, and Ye (2021) show that the only variable that significantly predicts passage of these laws in the cross section of states is the (age-adjusted) opioid overdose death rate, while economic conditions or political economy do not seem to play a role. We find similar evidence when replicating their analysis.

and Abraham (2021a). Importantly, as our identifying assumption, we show that states for which the law has passed, and the ones for which it has not, are on parallel trends in terms of home value changes before the passage of the law.[7] Last, we implement a Goodman-Bacon (2021) decomposition and show that our estimates receive a greater weight from the difference between *treated* units and *untreated* ones. This provides further assurance to our estimates, as these differences provide arguably the cleanest comparison.

Since our *treatment* is at the state level, we interact the passage of the state laws with measures of opioid supply at the county level to have a measure of treatment intensity at the same level as the observed outcome. First, we show that the prescription reduction in treated states is driven by the counties with the highest *ex ante* opioid supply within a state, as proxied by the number of ex-ante physicians per capita, and by opioid related payments to physicians by pharmaceutical companies, respectively.[8] Second, we find that home values rise significantly more in these counties upon the passage of the law. Taken together, these results suggest that variation in opioid prescription rates mostly drive the observed change in home values at the county level, and not the other way around.

To explore the possible underlying mechanisms driving the link between opioid prescriptions and home value changes, we study the effect of opioid usage on delinquent mortgages, vacancy rates and home improvement loans. Delinquent mortgages have been shown in the literature to have an impact on home values and could generate negative price spill overs to non-distressed neighbouring houses (e.g Gupta, 2019; Campbell, Giglio, and Pathak, 2011; Anenberg and Kung, 2014). We show that following the staggered adoption of opioid limiting laws the rate of change in mortgage delinquency rates was by about 6.17 percentage points lower on average one year after

[7] We also show that the confidence interval of the t=+2 coefficient falls outside of a linear trend based on 50% power following Roth (2022).

[8] Finkelstein, Gentzkow, Li, and Williams (2022) show that number of physicians per capita is a significant predictor of the propensity to prescribe opioids at the county level, while Engelberg, Parsons, and Tefft (2014) find similar evidence in case of opioid related payments to physicians by pharmaceutical companies.

the passage of the laws in *treated* counties, relative to the control group. We also find that the relative percentage of home improvement loans increased, while the residential vacancy rates decreased significantly more one year after the passage of the laws in *treated* counties, relative to the control group.

In additional analysis, we show that counties that had a higher exposure to opioid usage, subsequently experience a larger outflow of (high-income) households, relative to those with lower exposure to the opioid crisis. This set of results suggests that the degree of impoverishment in response to opioid abuse encourages the unaffected to leave and the affected to stay, consistent with Ambrus, Field, and Gonzalez (2020) predictions. These findings also illustrate the potential economic costs of spatially correlated shocks induced by a pandemic (Gupta, Mittal, Peeters, and Van Nieuwerburgh, 2022), when there are significant externalities from neighbours' socio-economic status. Passage of opioid-limiting laws reverses this trend: following treatment, we observe a significantly larger population and income inflow into treated counties. Taken together, our findings suggest a broader set of channels in which lost labor productivity and household income are one of the drivers of how opioid abuse impacted home values via delinquent mortgages and lower home improvement investments, but also through negative externalities which resulted in spatial redistribution of households.

In additional tests, we address potential measurement concerns and use additional empirical strategies. We use different proxies for opioid abuse, including opioid-related overdose deaths, and we find similar results to our baseline estimates. We also show similar results when we exclude counties that are most likely to contain "pill-mills".

As an additional approach to the difference-in-difference estimate, we utilize spatial regression discontinuity design to estimate the impact of opioid-limiting laws. We compare border counties in states that passed the laws with neighboring counties on the other side of the state border that were not subject to this change. Our results are consistent with the difference-in-differences estimates.

Because our main approach exploits negative variation in opioid usage driven by the passage of the laws, we use an additional alternative methodology that uses positive variation. We follow Cornaggia, Hund, Nguyen, and Ye (2022) and use instrumental variables to estimate the impact of opioid abuse on home values. We instrument opioid abuse using two alternative sources of variation. The first instrument is based on the aggressiveness of Purdue marketing of the product Oxycontin, which induced excessive prescription rates. The second one is based on "leaky" supply chains and the desirability of the product by patients when compared to less available and less attractive pain killers. Overall, the findings using this instrumental variable approach provide support for our baseline results.

Estimating the aggregate economic effects using our empirical approach is a challenging task, given the absence of a general equilibrium model. Although beyond the scope of our study to propose such model, we present back-of-the-envelope calculations of the aggregate economic impact based on our estimates, assuming no other effects of health on wealth and general equilibrium considerations that may have occurred in the economy due to regulatory changes. Our findings indicate that the loss in housing wealth induced by the opioid epidemic between 2006 and 2018 was at least $146 billion, using county and year variation, or $36 billion using state-year variation. By contrast, in 2022, Purdue Pharma agreed to pay $6 billion as part of the settlement to compensate several US states for the damages associated with the opioid crisis.

4.1.1 Literature

Existing evidence on drivers of demand for opioid prescriptions has been mixed.[9] Most of the literature suggests that the observed patterns in opioid usage have been driven by variation in supply of prescription opioids. Since Case and Deaton (2015) a number of studies have shown that economic conditions are not a significant driver of regional patterns of opioid use. In fact, most deaths attributed to opioid abuse

[9]See Maclean, Mallatt, Ruhm, and Simon (2020) for a review

occur in states with low unemployment rates (Currie, Jin, and Schnell, 2019). Finkelstein, Gentzkow, Li, and Williams (2022) show that the differences in the supply of prescription opioids from doctors is a key contributor to opioid abuse, as opposed to patient-specific factors such as mental health or poor economic prospects. The idea that supply-side factors are important determinants of opioid abuse is corroborated by Alpert, Evans, Lieber, and Powell (2021), who show that the introduction and marketing of OxyContin were important determinants of the opioid crisis. Paulozzi, Mack, and Hockenberry (2014) conclude that opioid prescription rates cannot be explained by variation in the underlying health of the population and instead suggest that the patterns reflect the lack of a consensus among doctors on best practices when prescribing opioids.

Our paper contributes to the rapidly growing literature on the impact of the opioid crisis on the U.S. economy. Harris, Kessler, Murray, and Glenn (2019), Van Hasselt, Keyes, Bray, and Miller (2015) and Florence, Luo, Xu, and Zhou (2016) study the impact of the opioid epidemic on human capital. They show a negative impact of opioid prescriptions on labor supply and quantify the costs associated to lost labor productivity. Agarwal, Li, Roman, and Sorokina (2022), Cornaggia, Hund, Nguyen, and Ye (2022), Ho and Jiang (2021), Li and Zhu (2019), Li and Ye (2022), and Jansen (2022) document financial effects of the crisis, including the impact of opioid abuse on municipal bond rates, firms' stock prices, banks' deposit growth, and consumer credit. Our paper focuses on the impact of the opioid crisis on real estate prices, which is a key indicator of the local economic situation and the most valuable asset on most households' balance sheet.

A few closely related papers also investigate the relationship between the opioid crisis and the local real estate market. Karimli (2022) and Luo and Tidwell (2023) study the implication on the mortgage market and find that lenders are less likely to approve loans from areas with higher rates of opioid abuse. Karimli (2022) further suggests that depressed local house prices by the opioid epidemic have been aggravated by resulting in more defaults using a sample between 2004 and 2017. Ho and Jiang (2021)

document a positive impact on real estate prices in Califronia between 2010 and 2018 following regulation that intends to limit opioid overuse, but do not analyse the underlying channel. D' Lima and Thibodeau (2022) use prescription data from Ohio between 2006 and 2012 to document a negative association between home values and opioid usage. Our paper analyzes the magnitudes of these effects, as well as the economic mechanisms behind it, using a national data sample and an identification strategy based on the staggered introduction of opioid supply regulation focusing on a later stage of the opioid crisis.

More broadly, we contribute to the literature that examines the effects of public health conditions on real estate and asset markets, i.e., the impact of health on wealth. Tyndall (2021) studies house price effects of legalized recreational marijuana in Vancouver, Canada, and finds that introduction of marijuana dispensaries imposes a negative price effect on nearby properties. Wong (2008) investigates the effect of the 2003 Hong Kong Severe Acute Respiratory Syndrome (SARS) epidemic on housing markets to find that prices declined by 1%-3% for affected housing complexes. Using data from 7th-century Amsterdam plague-, and 19th-century Paris cholera outbreaks, Francke and Korevaar (2021) show that the outbreaks resulted in large declines in home values, and smaller declines in rent prices. Our paper belongs to the nascent line of research that studies the effects of (global) pandemics on real estate and housing markets (Gupta, Mittal, Peeters, and Van Nieuwerburgh, 2022).

4.2 Opioid crisis background

The opioid crisis in the US evolved in three waves (Maclean, Mallatt, Ruhm, and Simon, 2021). The first wave started in the mid-1990s and continued through 2010 and marked itself with an unprecedented increase in prescription opioids. In the 1980s the US medical community adopted a more aggressive approach to pain treatment. Further, the American Academy of Pain Medicine and the American Pain Society advocated for greater use of opioids, arguing that there were minimal long-term risk

of addiction from these drugs following the FDA approval of OxyContin (oxycodone controlled-release), a new prescription opioid, in 1995. The Joint Commission on Accreditation of Healthcare Organizations (TJC) further institutionalized this stance in 2001, determining that the treatment and monitoring of pain should be the fifth vital sign.[10] This paved a way for the creation of a new metric upon which doctors and hospitals would be judged.

The second wave from 2010 to 2013 was characterised by a widespread increase in heroin use and deaths. Concerns about the possible over-use of opioid prescriptions for chronic pain conditions gained attention in early 2000s and efforts to reduce opioid prescription may have partly contributed to the diversion of opioid prescriptions and the increase in heroin use.

The current third wave that started in 2013 manifests itself with a movement towards extremely addictive synthetic opioids, in particular fentanyl. Opioid prescription regulations have been tightening further. In 2014, the Agency for Healthcare Research and Quality (AHRQ) concluded that evidence-based medicine to support opioids' use in chronic non-terminal pain is limited at best (Chou, Deyo, Devine, Hansen, Sullivan, Jarvik, Blazina, Dana, Bougatsos, and Turner, 2014). In 2016, the CDC issued a new policy recommendation for prescribing opioids advising amongst others to maximize non-opioid treatment.[11] To address the opioid epidemic the TJC revised and issued new standards on the treatment of pain in 2017.[12] In October of 2017, the US government declared opioid crisis a public health emergency.

Several states have taken specific action to address the opioid epidemic. First measures involved the development of prescription drug monitoring programs (PDMPs) with the goal of enabling doctors to better identify drug-seeking patients. However, many of these programs relied on voluntary participation of providers and they were not welcomed by physicians with, at best, mixed evidence on their effectiveness (Buch-

[10] https://www.medpagetoday.com/publichealthpolicy/publichealth/57336
[11] https://www.cdc.gov/mmwr/volumes/65/rr/rr6501e1.htm
[12] https://www.jointcommission.org/standards/r3-report/r3-report-issue-11-pain-assessment-and-management-standards-for-hospitals/

mueller and Carey, 2018; Meara, Horwitz, Powell, McClelland, Zhou, O'malley, and Morden, 2016; Islam and McRae, 2014). Recent measures were more drastic adopting legislation that explicitly sets limits on opioid prescriptions (with some exceptions such as cancer treatment or palliative care). In 2016, Massachusetts became the first state to limit opioid prescriptions to a 7-day supply for first time users. As of 2018, 32 states have legislation limiting the quantity of opioids which can be prescribed. A description of the state laws and regulations in a map is included in Appendix C.1. These laws seem to be more likely to pass in states that suffer from high rates of deaths related to opioids, as shown in Appendix Table C.I, while other potential determinants such as local economic, health and political characteristics do not seem to be correlated. At the federal level, Medicare also adopted a 7-day supply limit for new opioid patients in 2018.

4.3 Data

We use several different data sources in our main analysis. We proxy for local opioid abuse with historic opioid prescriptions. The Centres for Disease Control and Prevention reports county level opioid prescriptions sourced from IQVIA Xponent starting in 2006. IQVIA Xponent collects opioid prescriptions as identified by the National Drug Codes from approximately 49,900 retail (non-hospital) pharmacies, which covers nearly 92% of all retail prescription in the United States. Our key independent variable, prescription rate, is the count of annual opioid prescriptions at the county level per 100 people. Panel A in Table 4.1 reports summary statistics. Our data covers an average of 2,823 counties per annum over the 2006-2018 period. The average prescription rate corresponds to 82.6 opioid prescriptions per 100 people. Average prescription rates and county variation are consistent with the literature and other data sets (Currie, Jin, and Schnell, 2019; Harris, Kessler, Murray, and Glenn, 2019; Ouimet, Simintzi, and Ye, 2021).

To measure average annual home values of a typical house within a county, we use

the 2019 revision of the Zillow Home Value Index (ZHVI). This smoothed, seasonally adjusted measure incorporates property hedonic characteristics, location and market conditions from more than 100 million US homes, including new constructions, as well as non-traded homes, to compute the typical value for homes in the 35th to 65th percentile within a county. We calculate 1 to 5-year percentage changes in home values to allow initial prescriptions rates to turn into the onset of drug abuse. From 2006 to 2018, the ZHVI covers on average 2,575 counties per year. The average home value across counties was $140,000 and grew by 1.5% over one year, respectively 5.4% over 5 years with considerable cross-sectional variation (compare Panel B in Table 4.1).

We collect additional county-level demographic and economic variables for our analysis. Demographic variables include male population ratio, white population ratio, black population ratio, Indian American population ratio, Hispanic population ratio, age 20-64 ratio, age over 65 ratio and migration flow and are obtained from the Census Bureau. Neoplasms mortality is obtained from CDC. The number of primary care physicians excluding hospital residents or age 75 years or over is obtained from the Area Health Resources Files of the Health Resources & Service Administration. Economic variables include poverty ratio and median household income obtained from the Census Bureau, as well as unemployment rate and labour force participation rate obtained from Bureau of Labour Statistics. These variables are normalized by contemporaneous county population and winsorized at the 2 and 98 % level.

Starting with Massachusetts in 2016, several states passed laws or regulations to limit opioid prescriptions.[13] We collect information on the limits and the year of the passage of these opioid prescription limiting state laws.[14] Including Massachusetts, 9 states passed legislation that imposed limits on opioid prescriptions in 2016, while 18 states followed in 2017 and another 5 in 2018. Figure C.I pictures the treated states on a map

[13] We consider both laws and regulations as they are similar in their restrictions and both legally binding. We refer to them jointly as law. If multiple laws were passed by both the house and senate, we consider the year of the first law passed as it initiated the first restrictions. Laws differ in the level of restrictions. However, all laws, even if a second law was passed, limit opioid prescriptions.

[14] For an overview of the laws https://ballotpedia.org/Opioid_prescription_limits_and_policies_by_state

and Table C.II translates this into county observations.

To measure opioid supply side drivers at the county level, we use the data on the number of primary physicians per capita and collect data on direct or indirect payments or other transfers of value made from pharmaceutical and medical device manufactures and their distributors to physicians, non-physician practitioners, and teaching hospitals. Data on physician opioid related payments come from the Centers for Medicare & Medicaid Services Open Payments database, and it covers August 2013 to December 2019.[15] To compute opioid-related physician payments by the manufacturers, we follow Fernandez and Zejcirovic (2018) and Hadland, Rivera-Aguirre, Marshall, and Cerdá (2019): we identify opioid related payments through the National Drug Code (NDC) directory published by the U.S. Food and Drug Administration (FDA), which includes information on the substance names included in drugs.[16] We then use the substance names to identify opioid drugs following the Anatomical Therapeutic Chemical (ATC) Classification System of the WHO (ATC code N02A).[17] If a payment occurred for multiple drugs, we split the amount paid by the number of drugs promoted. We consider all payments made to physicians and teaching hospitals related to the identified opioid drugs. We identify the county of the physician or teaching hospital based on unique city and state combinations. If this is not possible, we use the Zipcode and assign the county based on the zipcode centeroid. Last, we aggregate by county and year. Counties without payments related to opioid payments are set to 0, as the coverage is US wide and no information is therefore equivalent to no payments.

[15] Source: https://www.cms.gov/OpenPayments/Data/Dataset-Downloads
[16] https://www.fda.gov/drugs/drug-approvals-and-databases/national-drug-code-directory
[17] https://www.whocc.no/atc_ddd_index/?code=n02a

4.4 Results

4.4.1 Opiod abuse and home values

4.4.1.1 Correlation between home values and prescription rates

We first document the correlation between home values and opioid abuse, as proxied by prescription rates. We exploit within county variation as well as within state-year variation. Figure 4.1 presents county-level heat maps of 5-year lagged county prescription rates and 5-year percentage change in home values for the year 2018, the last year in our sample with most observations. The maps show that counties in the bottom quintile of percentage change in home values overall correspond to the counties with the highest prescription rates, suggesting a negative correlation in the cross-section between prescription rates and 5-year percentage change in home value.

We further examine this relationship by estimating the following specification:

$$PCHomeValue_{c,t-x\ to\ t} = \alpha + \beta PrescriptionRate_{c,t-x} + \gamma Controls_{c,t-x} + \theta_c + \tau_t + \epsilon_{ct} \tag{4.1}$$

The dependent variable $PCHomeValue_{c,t-x\ to\ t}$ in equation 4.1 is the log percentage change of average county c home values, $(log(HV_t/HV_{t-x}) * 100)$ over $X = \{1,2,3,4,5\}$ years. $PrescriptionRate_{c,t-x}$ captures county c prescription rate at $t-x$. We also include a vector of time-varying county-level controls $Controls_{c,t-x}$, measured with a lag at time $t-x$. Following Ouimet, Simintzi, and Ye (2021), county-level controls measured at $t-x$ include: Male population ratio, white population ratio, black population ratio, American-Indian population ratio, Hispanic population ratio, age 20-64 ratio, age over 65 ratio, migration Inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and number of physicians per

county. We include county fixed effects θ_c, and control for general macro-economic conditions by including year fixed effects τ_t. In addition, in a separate specification, we use state-year fixed effects $\zeta_{s,t}$ instead of θ_c and τ_t to control for time-varying local market conditions.

Figure 4.2 shows the results of estimating Equation 4.1. Panel A includes county fixed effects θ_c, and year fixed effects τ_t, whereas we use state-year fixed effects $\zeta_{s,t}$ in Panel B.

We find that home values and prescription rates are negatively correlated in the short run. This negative association is persistent and stronger in the long run. The estimated coefficients for the correlation between prescription rates and changes in average home value are monotonically decreasing over 1 to 5 years. The correlation between prescription rates and 1 year percentage change in home values is estimated at -0.011, while the correlation with 5-years changes is -0.033, when exploiting within county variation. A one standard deviation increase in prescription rates translates in 1.35 percentage points reduction in home value growth rates, which is equivalent to 25.2% of the 5-year average percentage home value increase (5.36%). Point estimates obtained from within state-year variation are at -0.002 for 1-year change in home value and -0.008 for 5-year change in home value. Taking a one standard deviation change of prescription rates over 5 years translates into a 0.33 percentage points decrease in home values over the same period.

4.4.1.2 Adoption of opioid-limiting state laws: difference-in-differences estimates

In this section we exploit variation in opioid usage induced by the staggered adoption of state laws limiting prescriptions to estimate the impact of opioid abuse on home values.

We start by examining the link between the passage of the laws and actual opioid prescription rates to establish the effectiveness of the law changes. We implement a difference-in-differences framework to compare changes in county opioid prescription

rates in years before and after the passage of the law (*the treatment*) in *treated* versus *control* counties. We run a regression with lead and lag dummies relative to the year of the passage of the law to establish the path of total county prescription rates, and changes in home values and delinquent mortgages, before and after the law.

The literature on staggered differences-in-differences design (e.g. Callaway and Sant'Anna, 2021; Sun and Abraham, 2021a) highlights that running a staggered regression only with lead and lags are potentially problematic. First, weights across treatment cohorts can be non-intuitive and at worst negative, as they are proportional to group sizes as well as the variance of the treatment dummy in each pair. Second, already treated units act as controls for newly treated units, which is particularly problematic for trend break effects rather than unit shifts. We follow the Sun and Abraham (2021a) approach to estimate cohort-specific average treatment effect on the treated $(CATT(e,\ell))$, ℓ periods from initial treatment for cohort first treated at time e. Our baseline specification to estimate the impact of the passage of the laws on opioid prescriptions across time and states therefore is:

$$PrescriptionRate_{c,t} = \alpha + \sum_{e \in \{16,17,18\}} \sum_{l=-5,\neq -1}^{2} \delta_{e,l} \mathbf{1}\{E_i = e\} D_{ct}^{\ell} + \gamma Controls_{c,t-1} + \theta_c + \tau_t + \epsilon_{c,t} \tag{4.2}$$

The dependent variable $PrescriptionRate_{c,t}$ is defined as county prescription rates in year t. τ_t and θ_c are time and unit fixed-effects, representing calendar year and county fixed effects. $D_{i,t}^{\ell}$ are relative period indicators, that are equal to one for a county calendar year observation, where the time relative to the passage of the law statement matches the dummy statement, and zero otherwise. For instance, the relative time period dummy minus 2, $D_{i,t}^{-2}$, is equal to one for any county in calendar year 2014 that passed a law in 2016. As standard, we drop the relative time period dummy "minus 1" to avoid multicollinearity and focus on the change around the passage of the law. Sun and Abraham (2021a) interact these standard lead lag dummies with cohort specific indicators; i.e. $\mathbf{1}\{E_i = e\}$. In our specification there are three cohorts, with states, respectively counties, implementing the opioid law in 2016, 2017 respectively 2018.

Thus, there are three dummies that are equal to 1 for counties that passed the law in the specific cohort year and zero for any other county. This allows us to estimate cohort-specific average treatment effects. We additionally include county controls as defined before.

We restrict t to 2013–2018 to focus on the years around the passage of the law with the first law being passed in 2016 and the last in 2018. Hence, for counties with the law passed in 2016, the relative time period goes from "minus 3" to "plus 2". For counties with the law passed in 2018, the relative time period goes from "minus 5" to "plus 0". Finally, we calculate the proposed interaction-weighted estimator by aggregating the cohort-specific coefficients across each relevant time by their sample share in the relevant time period.

We then apply the same framework to compare the changes in county-level home values in years before and after the passage of the law in *treated* versus *control* counties.

$$PCHomeValue_{c,t} = \alpha + \sum_{e \in \{16,17,18\}} \sum_{l=-5, \neq -1}^{2} \delta_{e,l} \mathbf{1}\{E_i = e\} D_{ct}^{\ell} + \gamma Controls_{c,t-1} + \theta_c + \tau_t + \epsilon_{c,t} \tag{4.3}$$

Where the dependent variable $PCHomeValue_{c,t}$ is a one-year percentage change in home values defined as in Equation 4.1. County controls are the same as in the previous specification. Standard errors are clustered at the state level, as the laws were introduced at the state level.

Figure 4.3 plots the estimates of the total interaction weighted coefficient for each relative time period with the 95% confidence interval. The full set of coefficients for each $CATT(e, \ell)$ as well as the coefficients for lead and lag indicators of the two-way fixed effects regression without cohort-specific indicators can be found in Table C.IV in the Internet Appendix C.3.2.

Panel A shows that prescription rates declined more on average after the passage

of the laws in *treated* counties, relative to the control group. [18] As shown in Panel B, *treated* counties also experienced a higher increase in home values, relative to untreated counties. Counties in states that passed a law saw their home values rise 0.42 percentage points more in the year of the passage of the law, 0.81 percentage points more in the first year, and 1.78 percentage points more in the second year after the passage of the law relative to control counties. These results suggest that the adoption of state laws limiting opioid abuse had the intended result in reducing opioid prescription rates. Importantly, they also had a significant effect on the housing markets, resulting in an increase in home values.

4.4.1.3 Pre-trends

An identifying assumption in our analysis is that states for which the law has passed (*treatment*), and the ones for which it has not (*control*), are on parallel trends in terms of home value changes before the passage of the law. Table C.I in Appendix C.1, consistent with Ouimet, Simintzi, and Ye (2021), shows that the only variable that significantly predicts the passage of these laws in the cross section of states is the (age-adjusted) opioid overdose death rate, while economic conditions or political economy are not significant. The fact that economic and political conditions do not seem to differ between treated and control states gives us confidence that it is likely that home value changes were on a similar growth pattern prior to the passage of the law. Further, Figure 4.3 suggests that the parallel trend assumption is not violated.[19]

Still, Roth (2022) highlights that such a pretest may fail to detect preexisting trends that produce meaningful bias in the treatment effect. We follow Roth (2022) to identify whether our pre-test is likely to be effective. To assess whether our pre-test is likely to be well powered against violations of parallel trends, we plot a linear violation in Figure C.III in Appendix C.1 with a hypothesized slope based on having 50% power,

[18] In Figure C.II in the Appendix we show that despite overdose death rates increase after the passage of the law, its growth rate decreases.

[19] A related additional assumption is that no other laws that eventually passed at the same time had an impact on home values.

i.e. the probability of passing the pre-test is 50%. The estimated slope is 0.267, meaning that treated states' home values rise every year by 0.267 percentage points more relative to control states. Given a 1-year average percentage change in home values of 1.45% and a standard deviation of 4.53%, we consider this an economically meaningful deviation. The likelihood ratio for this hypothesized trend is 0.568, i.e. the chance of seeing the observed pre-test coefficients under the hypothesised trend relative to under parallel trends is only about half. Further, the 95% confidence interval on the point estimate on percentage change in home value in $t = +2$, is outside of expected coefficient (in blue) we would find based on the hypothesized trend. This result gives us confidence that our pre-test is reasonably effective.

4.4.1.4 Rents

Given that house prices represent the sum of the discounted cash flows these assets produce, in this subsection we ask a related question: what effect did opioid abuse have on rents? We estimate Equation 4.3, with change in the median county rent as the main dependent variable[20]. As we can see from Figure C.IV, following the introduction of opioid limiting laws, median county rents significantly increase 2 years after the passage of the laws.

4.4.1.5 Goodman-Bacon decomposition

Goodman-Bacon (2021) highlights that the general estimator from a two-way fixed effects approach is a "weighted average of all possible two-group/two-period (2x2) DiD estimators". The main coefficient is therefore a combination of many different treatment effects with possible non-intuitive and, at worst, negative weights. To understand which 2x2 DiD estimators drives the aggregate results, we implement a Goodman-Bacon (2021) decomposition. We run the following regression with both

[20]We collect median gross county rent data from the American Community Survey 5-year Estimates data. Gross rent is the sum of the contract rent plus estimated average monthly cost of utilities and fuels.

prescription rates and home value changes as dependent variable:

$$DepVar_{ct} = \alpha + \beta_1 Post_{ct} + \gamma Controls_{ct-1} + \theta_c + \tau_t + \epsilon_{ct} \tag{4.4}$$

β_1 is the coefficient of interest. We have nine individual 2x2 DiD estimators. *Earlier* vs *Later Treated* 2x2 DiD estimators include *cohort 2016* vs *cohort 2017*, *cohort 2016* vs *cohort 2018*, and *cohort 2017* vs *cohort 2018*. *Later* vs *Earlier Treated* 2x2 DiD estimators include *cohort 2017* vs *cohort 2016*, *cohort 2018* vs *cohort 2017*, and *cohort 2018* vs *cohort 2016*. Finally, for the *Treated* vs *Untreated* 2x2 DiD estimators we have *cohort 2016* vs *Untreated*, *cohort 2017* vs *Untreated*, and *cohort 2018* vs *Untreated*. We calculate and then plot the weight each 2x2 DiD estimators takes in the total beta (β), as well as the individual coefficient of each 2x2 DiD estimator.

Figure 4.4 shows the decomposition for the two dependent variables prescription rates and percentage change in home values for the full sample. We can identify two patterns. First, the individual estimate from *Treated* vs *Untreated* units receive the greatest weight within the total beta. This is reassuring, as these are probably the cleanest comparisons. Second, coefficients from *Later* vs *Earlier Treated* tend to have the opposite sign compared to the other estimates in the home value decomposition. Given that the parallel trends in Figure 4.3 point towards a trend break rather than a unit shift, it is unsurprising that these "bad" comparisons take on the opposite sign. However, the weight attached towards these coefficients is small with less than 9% for the whole group. Hence, their impact on the total beta is marginal.

4.4.2 County level evidence

In our baseline results the treatment variable is defined at the *state* level, while the outcome variable (home values) varies at the *county* level. In this section, we exploit county-level variation in the propensity to dispense opioids *prior* to the passage of the law to define the treatment variable at the same level as the outcome. We use two

proxies for opioid supply at the county level. First, we follow Finkelstein, Gentzkow, Li, and Williams (2022), who show that the *number of physicians per capita* is positively correlated with opioid prescriptions and is one important supply factor of opioids. Second, we follow Engelberg, Parsons, and Tefft (2014) and use opioid-related pharmaceutical companies' payments to physicians as a proxy for physicians' propensity to prescribe opioid drugs. We estimate the following standard two-way fixed effect regression with calendar year τ_t and county θ_c fixed effects.

$$\begin{aligned} DepVar_{ct} =& \alpha + \beta_1 Post_{ct} + \beta_2 Post_{ct} \times OpioidSupply\ top\ tercile_c \\ &+ \gamma Controls_{ct-1} + \theta_c + \tau_t + \epsilon_{ct} \end{aligned} \tag{4.5}$$

We use both county prescription rates and home value changes as dependent variable $DepVar_{ct}$. To account for different propensities to supply opioids within a state and therefore different impacts of the law at the county level, we construct an indicator variable, $OpioidSupply\ \ top\ \ tercile_c$, that is equal to one for counties in the highest tercile based on a 5-year average number of physicians per capita (total opioid related payments to physicians, respectively) before the first passage of any state law, i.e. between 2011 and 2015. $Post_{ct}$ is an indicator variable that is equal to one for the county-years following the law introduction. Figure C.VI in Appendix C.3.2 visualise the top tercile on a United States map. The coefficient of interest is β_2, which captures the intensity of the opioid limiting laws on counties that were *ex ante* more exposed to opioid abuse, as proxied by the relative opioid supply. Table 4.2, Column 2 shows that the drop in prescription rates following the passage of the law was concentrated in the counties with the highest number of physicians per capita, in line with Finkelstein, Gentzkow, Li, and Williams (2022)'s findings. This finding is echoed in Column 3, where we proxy for opioid supply using county-level opioid related pharmaceutical companies' payment to physicians. While home value changes seem to increase following the passage of the laws across all counties, they were greatest in counties in the top tercile of physicians payments (Column 6). These results provide further county-level evidence that opioid limiting laws had the strongest home value effect in

counties that were ex ante more exposed to the opioid crisis.

4.4.3 Opioid abuse and home values: economic mechanisms

The evidence presented in the previous section shows that opioid abuse results in lower home values. The decrease in home value can be driven by a reduction in household income, and lower ability to service a mortgage, which may lead to default and, ultimately, higher vacancy rates in the most affected areas. In less extreme cases, drops in home value might be due to lack of maintenance, reflected in fewer home improvement loans. In this section, we explore these channels.

We collect data on the percentage of delinquent mortgages by 90 or more days by county and month from the Consumer Financial Protection Bureau. The underlying data comes from the National Mortgage Database and is aggregated at the county level. 90-day delinquency rates generally capture borrowers that have missed three or more payments and, hence, arguably capture more severe and persistent economic distress. The coverage of this measure is less extensive than our main data, covering only 470 counties across the US. Delinquency rates are only reported for counties with a sufficient number of sample records to avoid unreliable estimates. The average mortgage delinquency rate between 2006 and 2018 was 2.41%. The average 5-year percentage change was -66.98% (see Table C.III in Appendix C.2). The average reduction in mortgage delinquency rates in our sample is large, as the peek of delinquency rates was reached at the beginning of our sample in 2010. Since then, it has steadily declined. As we explore cross-sectional variation in delinquency rates in our analysis, this is not a first-order concern. In addition to these data, we also collect data on the number of home improvement loans from the Home Mortgage Disclosure Act (HMDA), and residential property vacancy rates from the United States Postal Service (USPS). We report summary statistics for these variables in Table C.III in Appendix C.2.

As depicted in Table 4.3 there is a significant positive long correlation between lagged

prescription rates and the percentage change in mortgage delinquency rates, as proxied by the percentage of mortgages that are 90 days plus past due. The correlation is economically meaningful. To interpret the economic magnitude, consider a mortgage delinquency rate of 2.41% (the average in our sample): over 5-years this would have decreased to 0.80% based on the average 5-year percentage change (-66.98%), as reported in Table C.III. Using the county and year fixed effects estimate (column 1), a one standard deviation increase in prescription rate (27.1 prescriptions per 100 people for the 5-year lagged sample) is associated with 22.69 percentage points higher rate of change of delinquent mortgages. Starting out at a 2.41% mortgage delinquency rate, delinquent mortgages would have decreased only to 1.34% (by -66.98% + 22.69% = -44.29%) instead of 0.80%. This result suggests that an increase in mortgage delinquencies following opioid abuse is a possible important channel of how opioid abuse translates into lower housing values.

We also document a negative correlation between home improvement loans and prescription rates. The estimated coefficient is -0.024 when state-year fixed effects are included and -0.175 when county and year fixed effects are included. This means that for a one standard deviation increase in prescription rates (43.3), the rate of change in home improvement loans at the county level is between 1.0 and 7.6 percentage points lower.

Last, we show a positive correlation between residential vacancy rates and prescription rates. The estimated coefficient ranges between 0.062 and 0.267, which represents an increase between 2.7 and 11.6 percentage points in the percentage change of vacancy rates for a one standard deviation increase in prescription rates (43.6).

To further explore these associations, we apply the same framework as in Equation 4.3 to compare the changes in delinquent mortgages, residential vacancy rates and home improvement loans in years before and after the passage of the law (*the treatment*) in treated versus control counties.

Figure 4.5 plots the estimated coefficients for these channels. We find that the rate of

change in mortgage delinquency rate is about 6.17 percentage points lower on average one year after the passage of the laws in *treated* counties, relative to control group. Similarly, the rate of change in home improvement loans is up to 30 percentage points higher two years after the passage of the law and the rate of change in vacancy rate is as much as 8.6 percentage points lower one year after treatment.

These results suggest that the adoption of state laws limiting opioid abuse had a significant effect on the housing markets, by reducing the relative percentage of delinquent mortgages and vacancy rates, while significantly increasing the number of home improvement loans, ultimately resulting in an increase in home values as already documented.

4.4.3.1 Migration

Motivated by the results that areas that are more affected by the opioid crisis become less attractive to live, in this section we study the impact of opioid abuse on migration out of the county. We expect that both impoverishment from opioid abuse and also the change in the quality of the area would have driven residents out. We collect county level outflow and inflow migration data from the Internal Revenue Service (IRS). The Statistics of Income Tax Stats estimate migration outflows and inflows based on year-to-year address changes reported on individual income tax returns filed. Three measures of migration are reported, namely total adjusted gross income, number of returns filed and number of personal exemptions claimed. We define them as ”total income”, ”number of households” and ”number of individuals” in line with the IRS.

Table 4.4 looks at the link between county level migration outflow and opioid abuse. In Panels A and B, we proxy for opioid abuse using 5-year lagged county prescription rates, whereas in Panel C we use opioid overdose death rates (as defined in Section 4.6.2). In Panel A, the dependent variable is 5-year change in migration outflow. Columns 1, 3 and 5 include county and year fixed effects, while columns 2, 4 and 6 include state-year fixed effects. In columns 1 and 2 we use the 5-year percentage

change in total household income outflow from the county, in columns 3 and 4 we use the 5-year percentage change in the number of households who have left the county, while in columns 5 and 6 we use the 5-year change in the number of individuals who have left the county. Across the columns, we can see that an increase in the 5-year lagged county prescription rates is associated with an increase in the subsequent 5-year change in the number of households (individuals) who leave the county, as well as with the total household income outflow. While in columns 1, 3 and 5 the estimated coefficients are imprecisely estimated, in columns 2, 4 and 6 they are significant at the 99% level. In Panel B, we use the natural logarithm of the total household income (columns 1 and 2), of the number of households (columns 3 and 4), and of the number of individuals (columns 5 and 6), as the dependent variables. Similarly to results in Panel A, we see a positive relation between 5-year lagged prescription rates and the subsequent number and total income of households (individuals) who leave the county. While in columns 1, 3 and 5 the estimated coefficients are imprecisely estimated, in columns 2, 4 and 6 they are significant at the 99% level. In Panel C, we link whether the county is in the top tercile opioid overdose deaths in each year with the natural logarithm of the total household income (columns 1 and 2), of the number of households (columns 3 and 4), and of the number of individuals (columns 5 and 6), as the dependent variables. We obtain statistically significant coefficients at the 99% level in all specifications.

What kind of impact did opioid limiting laws have on migration in and out of the treated counties? Figure 4.6 shows the results of estimating Equation 4.2, with county migration inflow as the dependent variable. Panel A shows the results with natural logarithm of the total household income inflow, Panel B the natural logarithm of the number of households , and Panel C the natural logarithm of the number of individuals (columns 5 and 6), as the dependent variables. We can see that the treated counties experienced an inflow of (high-income) households following treatment, suggesting that positive income shocks had a desired effect on bolstering housing demand.

4.5 Discussion

4.5.1 Possible interpretations

Results from the previous section show that the passage of opioid-limiting laws is followed by a decrease in mortgage delinquencies and property vacancy rates, an increase in home improvement loans and population inflows. These effects are consistent with a decrease in defaults, an improvement in the quality of local real estate, and an increase in the local demand for space. This can be due to improving labour markets, as argued by Ouimet, Simintzi, and Ye (2021), or because of improvements in the area quality and economic conditions (Dougal, Parsons, and Titman, 2015).

Results of our empirical analysis are also consistent with a "spatial externalities" story à la Ambrus, Field, and Gonzalez (2020), according to which if a negative shock to a county is severe enough, there is an outflow of (high-income) households and the county tips into an equilibrium with relatively low-income households. In the context of the cholera-outbreak in one neighbourhood of nineteenth century London, Ambrus, Field, and Gonzalez (2020) model a rental market with frictions in which low-income households exert a negative externality on their neighbours. Similar to their setup, the opioid crisis affected people directly, not the local infrastructure (as would be the case in cases of hurricanes, or earthquakes).[21] In contrast to Ambrus, Field, and Gonzalez (2020), opioid crisis affected the whole country, with varying treatment intensities across counties.

Our findings are consistent with the Ambrus, Field, and Gonzalez (2020) model assumption that one of the channels of the effect of opioid abuse is an increase in the share of low-income households in affected counties through death or income-affecting disability of wage-earners. Our findings are also consistent with other direct channels, such as the opioid epidemic temporarily reducing local amenities in affected

[21] Note that opioid abuse can still affect local infrastructure indirectly.

areas, or inducing rich tenants having higher willingness to pay for such amenities to leave.

While the focus of Ambrus, Field, and Gonzalez (2020) model is to study the micro-location effects (within a neighborhood) of a temporary health driven (cholera outbreak) income shock, our paper examines the cross-county impact of opioid abuse.The main difference between Ambrus, Field, and Gonzalez (2020) set up and ours, is that their unit of analysis, blocks, are much smaller than our unit of analysis, counties. As such, there is more scope for different amenities (local institutions, local infrastructure, etc.) evolving in affected versus non-affected counties during the long period of opioid abuse in our case. As our results on mortgage delinquencies and home improvement loans indicate, this introduces other channels through which housing price differences can be explained.

4.5.2 Aggregate versus local economic effects of the opioid crisis

Estimating aggregate economic effects using our empirical exercise is admittedly challenging in the absence of a general equilibrium model. Although this is out of the scope of our paper, we provide back of the envelope calculations for aggregate economic impact based on our estimates, abstracting from other effects of health on wealth, as well as general equilibrium considerations that took place in the economy with, for instance, the changes in regulation. For this exercise, we take the agreement of the Sackler family to pay $6bn on a final settlement with several US states as a benchmark.[22] In 2022 they agreed to pay $6bn to compensate US states for the damages associated with the opioid crisis.

We provide a calculation based on our long-term correlations analysis. Between 2006 and 2011, US aggregate housing wealth decreased from $29.2 trillion to $22.7 trillion, which is equivalent to a -22.26% 5-year percentage change. Our estimates show that

[22]The Sacklers are the billionaire owners of Purdue Pharma, who have been widely blamed for helping to spark the US opioid epidemic with the marketing of OxyContin.

a one unit increase in prescription rates per 100 people for the 5-year lagged sample is associated to 0.033 percentage points reduction in house prices growth rates when using county and year fixed effects, and to a 0.008 percentage points reduction with state-year fixed effects.[23] Vowles, McEntee, Julnes, Frohe, Ney, and Van Der Goes (2015) find that rates of opioid misuse estimates from 38 studies between 2000 and 2013 averaged between 21% and 29% across most calculations. Assuming that 21% of prescription are misused, we calculate the aggregate housing wealth impact of a 21% opioid prescription rate reduction shock in 2006, i.e. a decrease from 72.4 prescription per 100 to to 57.2 per 100. The reduction of 15.2 prescriptions per 100 people for the 5-year lagged sample translates into a 0.50 percentage points increase in home value growth rates given the county and year fixed effects estimate, respectively an increase of 0.12 percentage points given the state-year fixed effect estimate. Thus, the US aggregate housing wealth would have decreased only by 21.76% (22.14%) to $22.85 trillion ($22.74 trillion). This equates to $146 billion ($36 billion) housing wealth lost. Figure 4.7 shows the aggregate housing wealth path from 2006 to 2018 as estimated by Zillow and for the 21% prescription rate shock in 2006 with county and year fixed effects, respectively state and year fixed effects. Figure 4.8 translates this into the actual gap in aggregate housing wealth lost. While the deviation from the path seems small, the actual estimated wealth lost is a two or even three digit billion dollar figure given the large aggregate housing wealth base.

We next make use of our natural experiment estimates. We first calculate one year percentage changes in house prices in 2016, 2017, and 2018 and adjust them for states by 0.423%, 0.810% and 1.781% respectively based on the year of the passage of the law. We next recalculate what state total home value would have been without the passage of the law. In the year of the passage of the law ($t = 0$), the aggregate value that all states gained is $69.57 billion (note that for some states this is in 2016, for some in 2017 and some in 2018). Taking just the states that passed the law in 2016, we can accumulate the home value difference over three years: aggregate home value would

[23] Zillow aggregate home value estimates: https://public.tableau.com/app/profile/zillow.real.estate.research/viz/TotalMarketValue/States

have been $184.54 billion lower without passing the law for a home value base of $5.91 trillion in 2015. For states that passed the law in 2017 and accumulating over two years this corresponds to $102.55 billion for a home value base of 7.78 trillion in 2016. Last, for states that passed the law in 2018 this corresponds to $11.70 billion for a home value base of $2.77 trillion in 2017.

4.5.3 Limits to internal and external validity

Our estimates, including aggregate effects rely on the internal validity of our quasi-natural experiment. We have discussed in Section 4.4 the formal identifying assumption of parallel trends. We assume that states that adopted the law (*treatment*), and the ones that did not (*control*), are on parallel trends in terms of home values before the treatment. In addition, we assume that no other changes in regulation have occurred simultaneously in treated states that affected both prescription rates as well as home values. Similarly, we assume no contamination between treated and control states. For instance, no migration of opioid users from treated to control states.

Our previous estimates for aggregate effects also rely on the external validity of our natural experiment and, as mentioned before, on potential general equilibrium effects as a result of the passage of the law such as the increased consumption of illicit drugs and potential migration of opioid consumers. Nevertheless, if taken into account, these effects would plausibly increase the magnitude of the estimated economic impact.

Importantly, comparing our back of the envelope housing wealth loss estimates with the value of the Sackler settlement reveals that the aggregate housing wealth effect of the opioid crisis is several orders of magnitude larger than the agreed settlement value.

4.6 Robustness

4.6.1 Alternative empirical strategies

4.6.1.1 State-border regression discontinuity design

In this section we employ a spatial regression discontinuity (RD) design exploiting state-border boundaries. In our estimation we compare counties located within a narrow distance from the state border under the assumption that border counties share otherwise similar general economic conditions. We define as *treated*, counties located in the state that passed opioid-limiting laws. The border distance of treated counties is measured to the nearest county where no opioid-limiting state law was passed. Formally, we estimate the following model:

$$y_c = \beta Treat_c + \sum_{p=1}^{P} [\gamma_{p0} + \gamma_{p1} Treat_c] Distance^p + \epsilon_{ct} \tag{4.6}$$

where y_c is a county level outcome, e.g. a 1 or 2 year difference in prescription rates or a 1 or 2 year percentage change in home values, $Treat_c$ is an indicator variable equal to one for counties in a state that passed opioid-limiting laws and $\sum_{p=1}^{P} [\gamma_{p0} + \gamma_{p1} Treat_c] Distance^p$ is a polynomial of order P (one or two) of the border distance (distance to the threshold). We calculate the percentage change from the *treatment year - 1* to the *treatment year*, and to the *treatment year + 1*, respectively for two year changes. For control counties, we calculate the difference (percentage change, respectively) from 2015 to 2016 or 2017, as the first law was passed in 2016. As controls, we include the following variables as of 2015: male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, which in this case corresponds to the distance

to the border. Standard errors are clustered at the state level.

Table 4.5 shows the results.[24] We show that treated counties show significant lower prescription rates when compared to control ones. Estimated coefficients for the difference in prescription rates over 1 year and 2 years are between 3.6 and 4.3 prescriptions per 100 people. This is a difference of about 5% evaluated at the mean. We then estimate the difference in terms of the percentage change in average home values over 1 and 2 years between treated and control counties around the border. The estimated coefficient is between 1.2 for one-year period and 2.2 for the two year period. Figure 4.9 shows the regression discontinuity plots. Results are overall consistent with previous differences-in-differences approach.

An important identifying assumption in our RD design is that there are no spill-over effects across the state borders. This would occur, for instance, if users can cross the border to fill their prescriptions, or due to "doctor shopping", when patients search (out of state) for doctors who will prescribe powerful medications. Although recent evidence suggests that only 0.7 percent of all patients with an opioid prescriptions are "doctor shoppers" (McDonald and Carlson, 2014, 2013), it might still be the case that patients can cross the border to have their prescriptions filled, which can bias our estimates upwards.[25] To address this concern we exclude counties with more than 8 "pill mill" pharmacies from our analysis. [26] Panel B of Figure 4.10 shows the results, which are overall consistent with the our main specification.

The internal validity of our quasi-experimental design relies on an important assumption that the treatment and control groups are similar, on average, in all other relevant aspects except for the treatment assignment, allowing us to isolate the causal effect of the treatment on the outcome. Figure C.V in the Appendix shows no significant differences in main economic variables across the state border, including our outcome variables, home values and prescription rates, before treatment.

[24] Results of estimating Equation 4.6 without control variables are shown in Internet Appendix Table C.V.
[25] States vary in how restrictive they are in filling out-of-state controlled substance prescriptions.
[26] See Section 4.6.2.1 for detailed definition of pill mill counties.

4.6.1.2 Purdue marketing and supply chain instrumental variables

Cornaggia, Hund, Nguyen, and Ye (2022) employ instrumental variables to establish causal effects of opioid abuse on municipal finance conditions. In this section, we follow their approach and apply two alternative instrumental variables. The first one is based on the aggressiveness of Purdue's marketing of the reformulated oxycodone (branded as OxyContin). The second is based on the "leaky" supply chains and the desirability of the product by addicts. We obtain data on the quantity of OxyContin distributed to 3-digit zip codes.[27] We calculate the percentage change in the quantity of OxyContin distributed by Purdue Pharma between 1997 and 2003 and use this as instrument for prescription rates after linking 3-digit zip codes to counties.

Table 4.6 shows the results. The first stage regression shows a strong positive association between the aggressiveness of Purdue marketing and prescription rates using a 4 and 5-year lag. In the second stage regression we find a negative effect of instrumented prescriptions on home values, which is consistent with our previous estimates. These estimates are significant when we cluster the standard errors by state and year, but not when clustering by county.

The second IV builds on two components. The first component is the type of opioid: we focus on those opioids with the highest addictive potential and the highest desirability to addicts. The second component is the distribution channel for these pills: we focus on pills sold through pharmacies with the least oversight and most potential for abuse – "leakiest" supply chains. Opioid abuse in contrast to more legitimate opioid use for treatment should be highest under such conditions. The Washington Post published detail pain pill transaction data between 2006 and 2014 based on the Drug Enforcement Administration's Automation of Reports and Consolidated Orders System.[28] Within this database, we focus on strong types of opioids, namely fentanyl, hydromorphone, levorphanol, oxycodone, and oxymorphone, that have the highest

[27] We thank Cornaggia, Hund, Nguyen, and Ye (2022) for sharing their data.
[28] https://wpinvestigative.github.io/arcos/

addictive potential and the highest desirability to addicts. Further, we consider only "retail" pharmacies as distribution channel, as retail pharmacies have the least oversight and therefore most potential for abuse. Within this opioid and distribution subset, we calculate the annual distribution of morphine milligram equivalent (MME) per county. Standardizing opioid strength using the MME value for each pill (e.g., oxycodone is 50% stronger than hydrocodone, so it has an MME multiplier of 1.5) allows us to account for for different dosages. Finally we scale the total annual distribution by 1000 county inhabitants.

Table 4.7 shows the results. We find a strong positive association between prescription rates and availability and desirability of opioids. The second stage regressions show a negative relation between prescriptions and home values, however these are not statistically significant at conventional levels.

Using instrumental variables has the advantage of using a source of exogenous variation in a variable that is endogenous. An identifying assumption of this methodology is that the instrument is not correlated with the outcome variable through any other channel but the one considered in the analysis. In this case we rely on the assumption that Purdue marketing aggressiveness and supply chain conditions are not related to local home values through any other economic mechanism than opioid abuse. The findings presented in this section using the IV approach provide support for our baseline results.

4.6.2 Measurement

Measuring opioid abuse accurately is challenging. We proxy opioid abuse via opioid prescriptions assuming that high levels of opioid prescription lead to opioid abuse due to its highly addictive nature. However, prescription rates may not lead to abuse *one for one*. Illnesses and the need for justified opioid prescription may differ by region, as well as the likelihood of opioid prescription turning into opioid abuse. Finally, opioid prescriptions may be distributed in one county, but consumed in another county. We

also use an alternative measure of opioid abuse by Cornaggia, Hund, Nguyen, and Ye (2022) and Li and Zhu (2019) is opioid mortality. Opioid mortality in a county implies a high addiction rate, albeit it only captures the most severe cases, because this outcome is at the very end of the addiction stage. We construct three measures of overdose death, $OpioidDeath$, namely annual drug overdose mortality rate per 100,000 residents, 3-year drug overdose mortality rate per 100,000 residents, and a dummy for counties in the top tercile for the 3-year drug overdose mortality rate per 100,000 residents.

Our key measure, $OpioidDeath$, is the drug overdose mortality rate per 100,000 residents. Following Cornaggia, Hund, Nguyen, and Ye (2022) and Li and Zhu (2019), we use data on county-level opioid mortality rates available in the Multiple Cause of Death data from the National Center for Injury Prevention and Control (NCIPC) of the Centers for Disease Control (CDC). The database complies county-level mortality data from 1999 based on the death certificates for all U.S. residents. Deaths are classified by the International Classification of Diseases, 10th Revision (ICD-10).We define drug overdose (or poisoning) deaths as those with ICD-10 underlying cause-of-death codes X40-X44 (unintentional overdose), X60-X64 (suicide by drug self-poisoning), X85 (homicide by drug poisoning), or Y10-Y14 (undetermined intent).

There are two potential limitations of this data set. First, the aggregate drug poisoning death counts include not only overdose deaths caused by opioid abuse but also deaths caused by other types of drugs with abuse potential (e.g., cocaine, methamphetamine, amphetamine, prescription stimulants). However, this is unlikely to confound our results because deaths involving opioids account for the vast majority of overall drug mortality in the U.S. While opioid deaths significantly increased during our sample period, deaths due to non-opioids drugs remain relatively stable. Second, if a county has fewer than 10 deaths in a given year, CDC data suppress the report of death counts to protect personal privacy. This implies that our overdose death rate is left-censored. To avoid potential biases arising from this censorship, we try to extend the coverage by focusing in addition to the annual overdose death rate on three-year overdose death

rates as well as on on a dummy capturing counties in the top tercile of overdose death rates, which allows us to extend the coverage by imputing overdose death rates for suppressed data, as described in Appendix C.3.3.

Since overdose deaths are at the end of the abuse timeline, we run to some extent contemporaneous regressions between the one-year percentage change in home values and overdose death rates:

$$PCHomeValue_{c,t-1\ to\ t} = \alpha + \beta OpioidDeath_{c,t} + \gamma Controls_{c,t-1} + \theta_c + \tau_t + \epsilon_{ct} \quad (4.7)$$

For instance, for the percentage change of home values between 2017 and 2018, we use the annual overdose death rate from 2018 and the three-year overdose death rate from 2016, 2017 and 2018 for both the quantitative variable and the top tercile dummy. Thus t corresponds to the last year of the three years for the three-year death rate. County controls are the same as in our main specification and are lagged by one year. As in our main specifications, we consider both county and year fixed effects as well as state-year fixed effects. We report results for counties with observations during the full sample period, i.e. 13 observations. Results are robust to considering all available county data. For the annual overdose death rate this leads to about 7,300 county-year observations, and about 11,800 respectively 17,500 county-year observations for the 3-year rate and 3-year rate dummy. Results are shown in Table 4.8.

Consistent with our previous estimates, changes in home values are negatively correlated to opioid abuse across all measures of overdose death and considering either fixed-effect specification. The results are more pronounced and significant for the 3-year overdose death rate top tercile dummy, which benefits from the largest sample. The percentage change in one year home values is 0.218 percentage points lower for counties in the top tercile of the 3-year overdose death rate, when using county and year fixed effects. The point estimate is 0.173 percentage points when using state-year fixed effects.

4.6.2.1 Excluding "pill mill" counties

Another limitation of using prescription rates as an opioid abuse measure is the potential misalignment between the prescription of the drug and intake. Drug consumers may have travelled miles to reach a doctor and pharmacy where they can receive a prescription and subsequently the drugs. A typical "pill mill" has a store front pain clinic with doctors prescribing opioids after a brief consultation, and usually limited proof of medical purpose. The prescriptions are often filled at the clinic to avoid other pharmacies challenging the legitimacy of the prescriptions. These pill mills are considered to have worsened the opioid crisis, as they were responsible for dispensing a large fraction of opioids.[29] Drug intake in pill mill counties is unlikely to be equivalent to prescription rates, leading to noise. Furthermore, pill mill counties may be correlated to weaker economic areas with implications for home value growths. These counties may therefore bias our analysis.

To address this concern we follow Ouimet, Simintzi, and Ye (2021) and drop counties that are most likely to have a pill mill. The Automation of Reports and Consolidated Orders System (ARCOS) data provides information on the milligrams of active ingredient (MME) dispensed by pharmacy.[30] We classify a pharmacy as a pill mill if it dispenses opioid MME in the top 5% of the sample. We then drop counties with more than 8 pill mills (equivalent to 6.3% of counties). Table 4.9 shows that our main results are robust to dropping "pill mill" counties.

[29] Between 2006 and 2012 15% of pharmacies received for instance 48% of pain pills, see https://www.washingtonpost.com/investigations/the-opioid-crisis-15-percent-of-the-pharmacies-handled-nearly-half-of-the-pills/2019/08/12/b24bd4ee-b3c7-11e9-8f6c-7828e68cb15f_story.html.

[30] The Drug Enforcement Agency (DEA) collected this data and made it available to the public following a FOIA lawsuit by the Washington Post. Only the two most common forms of opioid prescriptions, OxyContin and Hydrocontin, are covered.

4.7 Conclusion

This paper estimates the sensitivity of home values to opioid abuse. We find a negative association between home values and opioid abuse that is monotonically increasing and persistent over a 5-year period. We exploit variation in opioid abuse induced by the staggered passage of state laws that aim to limit these prescriptions as a source of variation in opioid prescriptions. Home values respond positively to the passage of the state laws intended to reduce opioid abuse.

We study possible underlying economic mechanisms for this relation. We find that opioid abuse is negatively correlated with the number of initiated home improvement loans, and positively correlated with vacant residential property rates and delinquent mortgages. Passage of effective anti-opioid legislation results in a decrease (increase) in mortgage delinquencies and property vacancy rates (the number of home improvement loans and migration inflows, respectively), consistent with a decrease in defaults, an improvement in the quality of local real estate, and an increase in the local demand for space being the main drivers of the observed effect. Our findings are also consistent residential sorting where further impact on house values can be rationalized through the associated outflow migration of people from areas that are most affected by the opioid crisis. Overall, our results point to a broad set of area externalities channel(s) driving the observed patterns in home values.

Our results have two main implications. First, they suggest that although opioid usage has been associated with low income and economically disadvantaged conditions (Case and Deaton, 2015), limiting the supply of prescription drugs has both a significant impact on reducing opioid usage, as well as a relevant economic impact, namely in positively affecting home values and reducing the percentage of delinquent mortgages. Second, lost labor productivity and thus household income may be one driver of how opioid abuse impacted home values via delinquent mortgages, but also through negative spatial externalities of opiod abuse which resulted in spatial redis-

tribution of households.

Our work offers insights into externalities of public health policies. We find evidence that public health policies that were instituted with the aim of limiting opioid abuse had a far reaching effect on the real economy. We believe that this study will foster further interest in examination of transmission and feedback effects of public health policies and real economic outcomes.

4.8 Tables

Table 4.1. Summary statistics

Our sample period covers 2006 to 2018. We report descriptive statistics for opioid abuse proxies in Panel A. This includes retail opioid prescriptions dispensed per 100 persons per year, total county level retail opioid prescriptions, annual drug overdose death rate per 100,000 residents considering ICD-10 underlying cause-of-death codes X40-X44 (unintentional overdose), X60-X64 (suicide by drug self-poisoning), X85 (homicide by drug poisoning), or Y10-Y14 (undetermined intent), as well as 3-year drug overdose death rate per 100,000 residents with the same cause-of-death codes that aggregates the deaths across three years. Panel B reports county level home value statistics: the raw estimated home value of a typical house within a county based on the 2019 revision of the Zillow Home Value Index (ZHVI), as well as 1, 2, 3, 4 and 5-year log percentage changes in county level home value.

	Panel A: Opioid abuse proxies								
	N total	Avg N Annual	Mean	Min	P25	Median	P75	Max	Std. Dev.
Prescription Rate (per 100)	36,704	2,823	82.60	4.20	53.20	77.80	106.90	198.99	42.48
County Prescriptions	36,704	2,823	71,802.60	301.05	8,895.14	26,982.68	75,065.89	582,964.53	117,074.74
Annual Drug Overdose Death Rate	12,990	999	18.82	4.70	11.05	15.83	23.49	56.51	11.14
3-year Drug Overdose Death Rate (in %)	20,073	1,544	17.02	5.24	10.61	14.96	21.01	46.59	8.94
	Panel B: Home values								
	N total	Avg N Annual	Mean	Min	P25	Median	P75	Max	Std. Dev.
Avg Home Value ($)	33,481	2,575	140,033.56	47,116.70	85,275.08	117,306.50	169,095.08	425,161.58	79,347.56
1-year Perc Change HV (in %)	30,633	2,553	1.45	-10.27	-1.40	1.91	4.66	10.23	4.53
2-year Perc Change HV (in %)	27,799	2,527	2.50	-19.42	-2.94	3.25	8.67	19.10	8.56
3-year Perc Change HV (in %)	24,990	2,499	3.38	-27.70	-4.33	4.09	12.04	27.19	12.07
4-year Perc Change HV (in %)	22,227	2,470	4.36	-33.35	-5.12	4.77	14.87	34.60	14.89
5-year Perc Change HV (in %)	19,524	2,440	5.36	-35.52	-5.54	5.33	16.75	41.10	16.85

Table 4.2. Opioid supply propensity interaction

The sample period is 2013 to 2018. The dependent variable is prescription rate in columns 1 to 3, respectively a log percentage change of average county home values over 1 year in columns 4 to 6. *Post* is a dummy equal to one in the year of the passage of the law in the respective county and thereafter; *Physicians per capita Tercile 3* is a dummy equal to one for counties whose average physicians per capita between 2011 to 2015 is in the top tercile and *Phys. Opioid Payment Rate Tercile 3* is a dummy equal to one for counties in the top tercile based on opioid related payments to physicians from August 2013 (data start) until the end of 2015. Controls include: Male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio and neoplasm mortality. We include county and year fixed effects. Standard errors are clustered at the state level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Prescription Rate			Percentage Change Home Prices		
Post	-2.533^{*}	-1.658	0.261	0.731^{**}	0.673^{**}	0.569^{*}
	(1.310)	(1.423)	(1.376)	(0.319)	(0.317)	(0.319)
Post X Physicians per capita Tercile 3		-2.266^{*}			0.148	
		(1.204)			(0.185)	
Post X Phys. Opioid Payment Rate Tercile 3			-5.998^{***}			0.346^{**}
			(1.415)			(0.160)
R2	0.950	0.950	0.950	0.589	0.590	0.590
N	15199	15199	15199	14695	14695	14695

Table 4.3. Economic mechanisms: Correlation with prescription rates

The sample period is 2006 to 2018.The regression specification and controls is the same as in Equation 4.1 but for the dependent variables. The dependent variable is a 5-year percentage changes in the mortgage delinquency rate (percent of mortgages 90 days plus past due) in columns 1 and 2, over 5 years, in the number of home improvement loans columns 3 and 4, and in the residential vacancy rates in columns 5 and 6. The key independent variable of interest is the lagged prescription rate. County controls include the male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. All independent variables are lagged over five years. All variables are winsorized at the 2 and 98 % level. Standard errors are clustered at the county level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	5-year percentage change in					
	Mortgage delinquency rate		No. of home improvement loans		Residential vacancy rate	
Lag Prescription Rate	0.837***	0.192***	−0.175***	−0.024**	0.267***	0.062***
	(0.188)	(0.047)	(0.045)	(0.010)	(0.047)	(0.022)
R2	0.904	0.901	0.672	0.661	0.758	0.337
N	2350	2320	14721	14794	9488	9589
Std. dev. prescription rate	27.11	27.08	43.29	43.34	43.55	43.63
County F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
State-Year F.E.	No	Yes	No	Yes	No	Yes

Table 4.4. Opioid abuse and migration outflow

The sample period is 2006 to 2018. The dependent variable is a measure of total migration outflow based on on individual income tax returns filed with the IRS. In column 1 and 2, it is based on the total adjusted gross income, in column 3 and 4 the number of households approximated by the number of returns filed and in column 5 and 6 the number of individuals approximated by personal exemptions claimed. In Panel A, we calculate 5-year percentage changes for the dependent variables and in Panel B and C we calculate logs of the dependent variable. In Panel A and B the key independent variable of interest is the 5-year lagged prescription rate. The specification therefore follows Equation 4.1 and takes the same 5-year lagged controls. The specification in Panel C follows Equation 4.7. We consider only the most populated opioid overdose measure as independent variable, namely "3-year overdose death rate top tercile". Controls are lagged by one year. Standard errors are clustered at the county level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 5-year lagged prescription rates and 5-year percentage change in migration outflow measures						
	Perc Change Total income		Perc Change no. households		Perc Change no. individuals	
Lag Prescription Rate	−0.005	0.008**	0.002	0.015***	0.001	0.015***
	(0.016)	(0.004)	(0.010)	(0.003)	(0.011)	(0.003)
R2	0.506	0.468	0.628	0.640	0.638	0.634
N	17208	17275	17222	17288	17222	17288
Panel B: 5-year lagged prescription rates and log migration outflow measures						
	Log(Total income)		Log(Households)		Log(Individuals)	
Lag Prescription Rate	−0.003	0.394***	−0.001	0.380***	−0.003	0.380***
	(0.013)	(0.023)	(0.008)	(0.027)	(0.009)	(0.027)
R2	0.989	0.825	0.995	0.809	0.994	0.806
N	17215	17281	17222	17288	17222	17288
Panel C: Opioid overdose death and log migration outflow measures						
	Log(Total income)		Log(Households)		Log(Individuals)	
3-year overdose death rate top tercile	0.613*	13.370***	0.648***	14.440***	0.836***	15.181***
	(0.355)	(2.020)	(0.226)	(2.025)	(0.240)	(2.009)
R2	0.991	0.863	0.996	0.817	0.995	0.812
N	18260	18250	18264	18254	18264	18254
County F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
State-Year F.E.	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.5. Opioid Law Impact on prescription and home values around state borders

The unit of observations are counties. In columns 1 to 4 we consider all counties. In columns 5 to 8 we exclude counties with more than 8 pill mills. We calculate one or two-year difference in prescription rate, respectively percentage changes in home values from the treatment year - 1 to the treatment year, respectively treatment year + 1. For control counties, we calculate the difference, respectively percentage change from 2015 to 2016 or 2017, as the first law was passed in 2016. As controls, we include the following variables as of 2015: male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth. Standard errors are clustered at the state level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All counties				Excluding pill mill counties			
	Difference in County Prescription Rates over ...							
	1 year		2 years		1 year		2 years	
RD Estimate	-4.219***	-4.176***	-4.004**	-3.544*	-3.972***	-3.837***	-3.794**	-3.269
	(1.004)	(1.099)	(1.771)	(2.047)	(1.062)	(1.174)	(1.914)	(2.188)
Observations	2389	2389	2066	2066	2210	2210	1923	1923
MSEBandwidth	94	165	115	186	93	163	113	186
Effective LHS Obs	504	754	574	783	479	714	545	744
Effective RHS Obs	546	872	474	695	507	804	439	645
Polynominal Order	1	2	1	2	1	2	1	2
	All counties				Excluding pill mill counties			
	Percentage Change in County Average Home Values over...							
	1 year		2 years		1 year		2 years	
RD Estimate	1.157*	1.195*	2.158*	2.165*	1.180*	1.257*	2.232**	2.279**
	(0.699)	(0.708)	(1.148)	(1.176)	(0.703)	(0.685)	(1.065)	(1.116)
Observations	2334	2334	2020	2020	2157	2157	1879	1879
MSEBandwidth	118	217	121	215	102	200	109	193
Effective LHS Obs	570	788	583	784	496	736	519	729
Effective RHS Obs	660	1041	498	769	544	918	427	666
Polynominal Order	1	2	1	2	1	2	1	2

Table 4.6. Instrumental variable: Purdue marketing

The sample period is 2006 to 2018. The depend variable is 4-year percentage changes in home values in Panel A and 5-year percentage changes in Panel B. We run a two-stage least squares regression with *Purdue Marketing* as instrument. *Purdue Marketing* is defined as growth in pill distribution between 1997 and 2003. Controls include: Male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio and neoplasm mortality. We also include state-year fixed effects. In columns 1 and 2 we cluster standard errors at the county level and in columns 3 and 4 at the state and year level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1) IV: Stage 1	(2) IV: Stage 2	(3) IV: Stage 1	(4) IV: Stage 2
Panel A: 4-year percentage change in home values				
Purdue Marketing	1.322***		1.322***	
	(0.298)		(0.116)	
Estimated Prescription Rate		−0.030		−0.030*
		(0.025)		(0.017)
R2	0.357	0.857	0.357	0.857
N	19726	17965	19726	17965
F-statistic	41.1	7.5	228.6	15.4
Panel B: 5-year percentage change in home values				
Purdue Marketing	1.329***		1.329***	
	(0.303)		(0.122)	
Estimated Prescription Rate		−0.039		−0.039*
		(0.031)		(0.021)
R2	0.362	0.857	0.362	0.857
F-statistic	17183	15532	17183	15532
N	39.6	7.4	215.0	16.1
State-Year F.E.	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Std. Error	County	County	State-Year	State-Year

Table 4.7. Instrumental variable: Supply Chain

The sample period is 2006 to 2018. The depend variable is 4-year percentage changes in home values in Panel A and 5-year percentage changes in Panel B. We run a two-stage least squares regression with leaky supply chains (*Supply Chain*) as instrument. *Supply Chain* is defined as annual MME per 1000 county inhabitants distribution of strong types of opioid to retail pharmacies. Controls include: Male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio and neoplasm mortality. We include state-year fixed effects in columns 1 to 4 and county and year fixed effects in columns 5 to 8. In columns 1, 2, 5 and 6 we cluster standard errors at the county level and in columns 3, 4, 7 and 8 at the state and year level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	8)
	State-Year F.E.				County & Year F.E.			
	Cluster County		Cluster state x year		Cluster County		Cluster state x year	
	IV: Stage 1	IV: Stage 2	IV: Stage 1	IV: Stage 2	IV: Stage 1	IV: Stage 2	IV: Stage 1	IV: Stage 2
Panel A: 4-year percentage change in home values								
Supply Chain	1.020***		1.020***		1.020***		1.020***	
	(0.065)		(0.071)		(0.065)		(0.071)	
Estimated Prescription Rate		−0.006		−0.006		−0.006		−0.006
		(0.007)		(0.006)		(0.007)		(0.006)
R2	0.413	0.839	0.413	0.839	0.413	0.839	0.413	0.839
N	14479	12910	14479	12910	14479	12910	14479	12910
F-statistic	59.3	8.5	175.6	10.7	59.3	8.5	175.6	10.7
Panel B: 5-year percentage change in home values								
Supply Chain	1.025***		1.025***		0.279***		0.279***	
	(0.065)		(0.071)		(0.042)		(0.031)	
Estimate Prescription Rate		−0.011		−0.011		−0.144		−0.144
		(0.009)		(0.007)		(0.092)		(0.158)
R2	0.415	0.845	0.415	0.845	0.948	0.796	0.948	0.796
N	14479	12910	14479	12910	14411	12840	14411	12840
F-statistic	59.4	8.2	175.6	14.1	7.4	37.2	13.0	17.9
County F.E.	No	No	No	No	Yes	Yes	Yes	Yes
Year F.E.	No	No	No	No	Yes	Yes	Yes	Yes
State-Year F.E.	Yes	Yes	Yes	Yes	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Std. Error	County	County	State-Year	State-Year	County	County	State-Year	State-Year

Table 4.8. Home value and overdose death rates

The sample period is 2006 to 2018. The dependent variable is a 1-year log percentage change of average county home values ($log(HV_t/HV_{t-1}) * 100$). *Overdose death rate* is the annual overdose deaths per 100,000 county inhabitants at t, *3-year overdose death rate* is the 3-year overdose death rates per 100,000 county inhabitants for the years t, $t-1$ and $t-2$, and *3-year overdose death rate top tercile* is a dummy equal to one for counties in the tercile with the highest 3-year overdose death rates. We restrict the sample to counties with data in every period. One year lagged controls include: Male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio and neoplasm mortality. Columns 1, 3 and 5 control for county and year fixed effects and columns 2, 4 and 6 for state-year fixed effects. We require counties to have data for the whole time series, i.e. the full 13 years, to avoid counties dropping in and out depending on suppressed data. Standard errors are clustered at the county level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	One-year percentage change in home values					
	(1)	(2)	(3)	(4)	(5)	(6)
Overdose death rate	−0.014*	−0.005				
	(0.008)	(0.005)				
3-year overdose death rate			−0.001	−0.008*		
			(0.009)	(0.004)		
3-year overdose death rate top tercile					−0.218**	−0.173***
					(0.093)	(0.052)
County F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
State-Year F.E.	No	Yes	No	Yes	No	Yes
R2	0.685	0.801	0.657	0.783	0.647	0.778
N	7288	7249	11773	11756	17467	17462
Std. dev. overdose variable	10.542	6.585	8.992	5.600	.469	.366

Table 4.9. Home value and opioid prescription rates: Correlations excluding counties with more than 8 pill mills

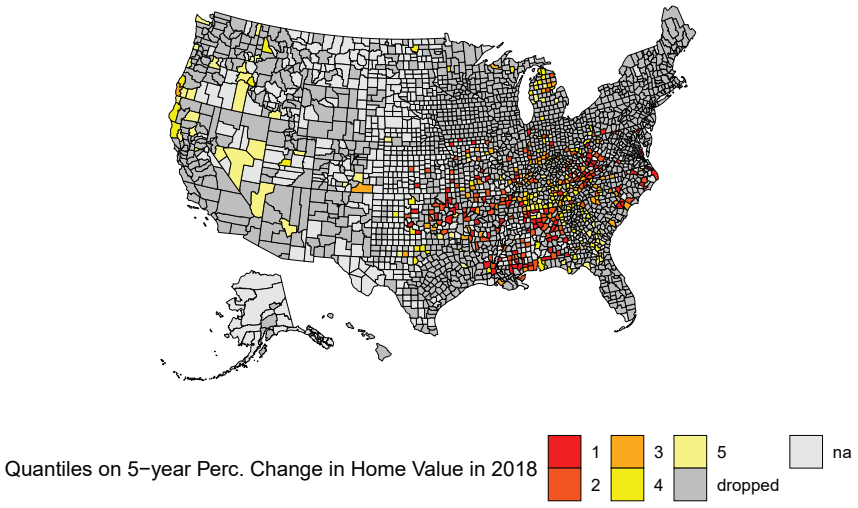
The sample period is 2006 to 2018.The regression specification and controls is the same as in Equation 4.1, but we drop counties with more than 8 pill mills, equivalent to dropping the top 6.3% counties based on the number of pill mills. The dependent variable is a log percentage change of average county home values ($log(HV_t/HV_{t-x}) * 100$) over 1, 2, 3, 4 and 5 years. County controls include the male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. All variables are winsorized at the 2 and 98 % level. Columns 1 to 5 include county and year fixed effects and columns 6 to 10 state-year fixed effects. Standard errors are clustered at the county level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Perc. Change Home Value									
	Lag over					Lag over				
	1 Year	2 Years	3 Years	4 Years	5 Years	1 Year	2 Years	3 Years	4 Years	5 Years
Lag Prescription Rate	−0.007***	−0.011***	−0.012*	−0.016*	−0.022**	−0.001*	−0.002**	−0.004**	−0.005**	−0.005*
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
County F.E.	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Year F.E.	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
State-Year F.E.	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R2	0.636	0.689	0.740	0.776	0.807	0.753	0.802	0.835	0.850	0.851
N	22930	20605	18279	15964	13743	22971	20656	18354	16059	13818

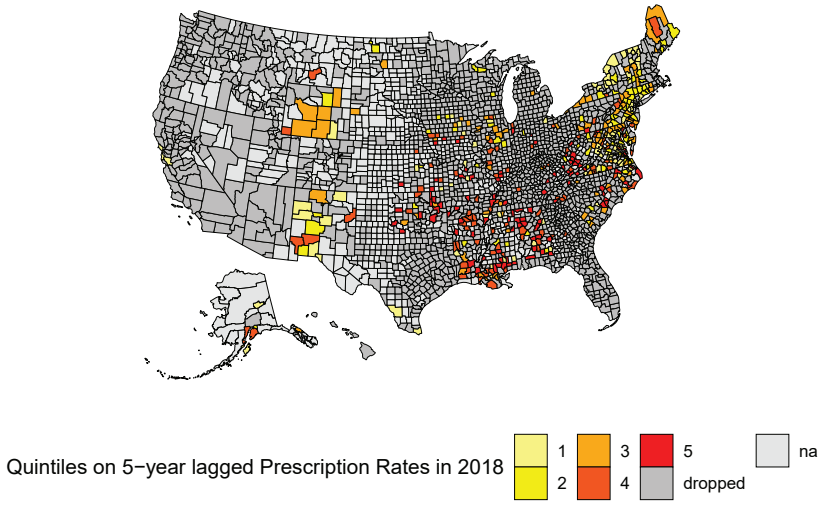
4.9 Figures

Figure 4.1. Home value and opioid prescription rate

We plot percentage changes in home value between 2014 and 2018 and prescription rates in 2014. This is the last year of our sample with the most observations. Panel A shows counties in the highest prescription rate quintile in 2014. Excluded counties are dark grey, counties without data are light grey. Heat colours for the remaining counties are based on the quintiles of the 5-year percentage change in home values from 2014 to 2018. Dark red represents the lowest percentage change in home values. Panel B shows counties in the lowest quintile of percentage change in home values and assigns heat map colors based on the prescription rate quintile in 2014. Dark red in Panel B corresponds to the highest prescription rate quintile.



(a) Counties in highest Prescription Rate Quintile colored by Percentage Change in Home Values

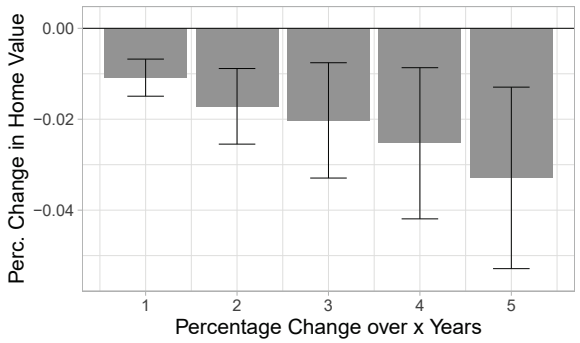


(b) Counties in lowest Percentage Change in Home Values Quintile colored by Prescription Rate

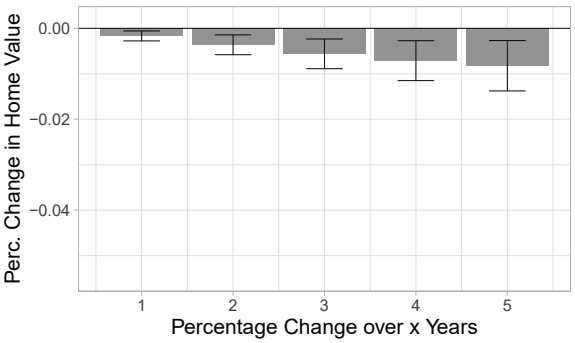
Figure 4.2. Home value and opioid prescription rate: Correlations

The sample period is 2006 to 2018. The dependent variable is a log percentage change of average county home values ($log(HV_t/HV_{t-x}) * 100$) over 1, 2, 3, 4 and 5 years. We report and plot coefficients and 95% confidence intervals on lagged prescription rates. County controls include the male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. Controls are lagged over the same period as the prescription rate. Panel A includes county and year fixed effects and Panel B state-year fixed effects. All variables are winsorized at the 2 and 98 % level. Standard errors are clustered at the county level.

(A) County & Year Fixed Effects



(B) State-Year Fixed Effects



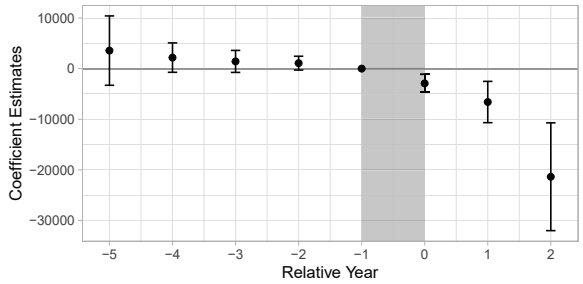
	over 1 year	over 2 years	over 3 years	over 4 years	over 5 years
x-year lagged Prescription Rate	-0.011*** (0.002)	-0.017*** (0.004)	-0.020*** (0.006)	-0.025*** (0.008)	-0.033*** (0.010)
Adj. R2	0.599	0.648	0.699	0.735	0.767
No. of Obs	25,026	22,510	19,993	17,487	15,075
SD Pres. Rate	41.203	41.670	42.136	42.459	42.620

	over 1 year	over 2 years	over 3 years	over 4 years	over 5 years
x-year lagged Prescription Rate	-0.002*** (0.001)	-0.004*** (0.001)	-0.006*** (0.002)	-0.007*** (0.002)	-0.008*** (0.003)
Adj. R2	0.759	0.806	0.838	0.854	0.854
No. of Obs	25081	22572	20077	17590	15157
SD Pres. Rate	41.247	41.714	42.216	42.563	42.640

Figure 4.3. The effect of opioid limiting laws on prescription rate and home values

The sample period is 2013 to 2018. The dependent variable is total county prescriptions in Panel A and the log percentage change in average county home values in Panel B. Controls include one year-lagged male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. In Panel A we additionally control for log county population. We plot the interaction weighted total coefficient with a 95% confidence interval for each relative time period following Sun and Abraham (2021a). Standard errors are clustered at the state level.

(A) County prescriptions



(B) Percentage Change in Average County Home Value (in %)

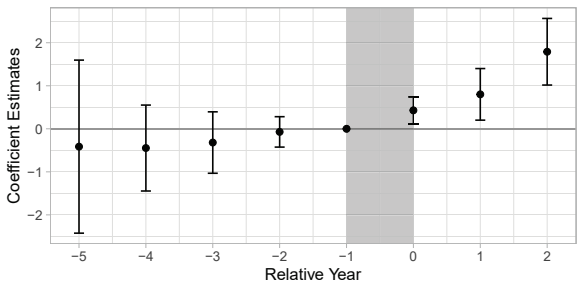
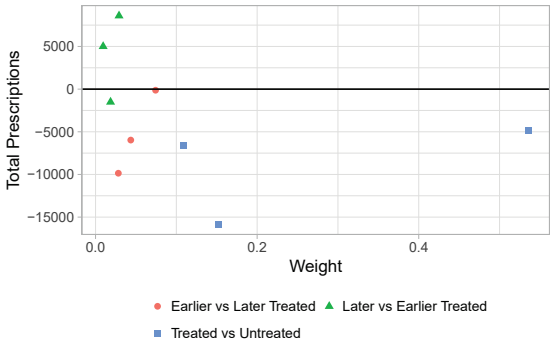


Figure 4.4. Goodman-Bacon decomposition

The sample period is 2013 to 2018. The dependent variable is *Prescriptions* in Panel A and *PCHomeValue* in Panel B. We show the Goodman-Bacon (2021) decompositions for the TWFE regression $Dep.\ variable_{ct} = \alpha + \beta Post_{ct} + \theta_c + \tau_t + \epsilon_{ct}$. We do not include any controls in the regression.

(A) County Prescriptions



(B) Perc. Change in Home Values

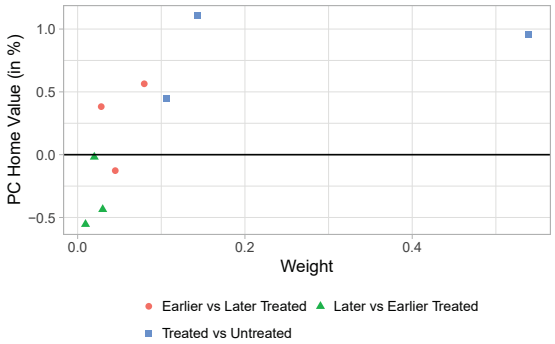
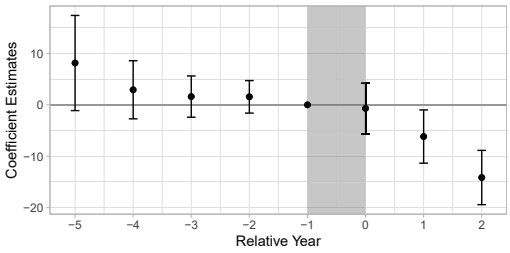
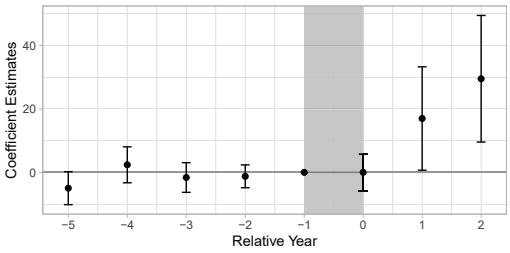


Figure 4.5. The effect of opioid limiting laws on year-on-year changes in delinquent mortgages, home improvement loans and vacancy rates

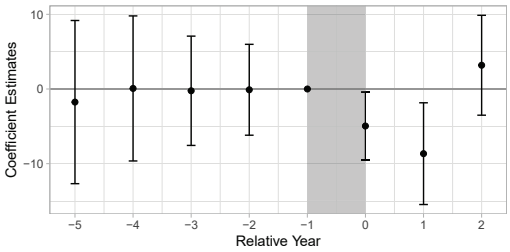
The sample period is 2013 to 2018. The dependent variable is the log percentage change in mortgages 90 plus days past due (in %) in Panel A, the log percentage change in the number of home improvement loans (in %) in Panel B and the log percentage change in the residential vacancy rate(in %) in Panel C. Controls include one year-lagged male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We plot the interaction weighted total coefficient with a 95% confidence interval for each relative time following Sun and Abraham (2021a). Standard errors are clustered at the state level.



(a) Mortgages 90 plus days past due



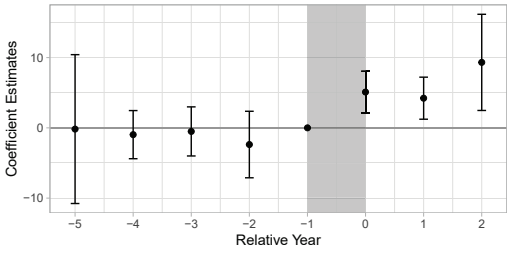
(b) Home improvement loans



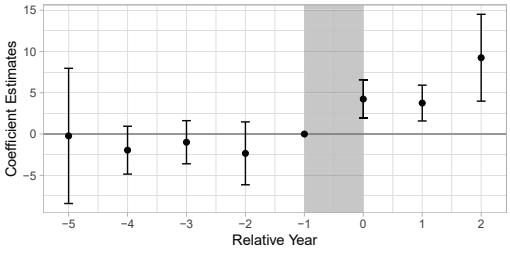
(c) Residential vacancy rate

Figure 4.6. The effect of opioid limiting laws on migration inflow

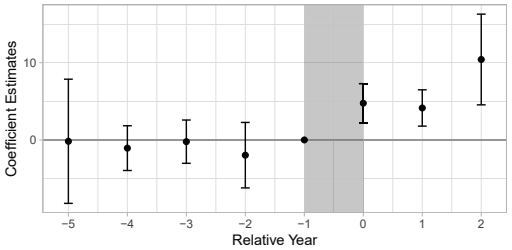
The sample period is 2013 to 2018. The dependent variable is the log total migration inflow income in Panel A, the log total migration inflow number of households in Panel B and the log total migration inflow number of individuals in Panel C. Controls include one year-lagged male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We plot the interaction weighted total coefficient with a 95% confidence interval for each relative time period following Sun and Abraham (2021a). Standard errors are clustered at the state level.



(a) Total income



(b) Number of households



(c) Number of individuals

Figure 4.7. Housing wealth over time

We report US aggregate housing wealth by year as well the path estimated with a 21% prescription rate reduction shock in 2006 and the same housing wealth growth rate thereafter.

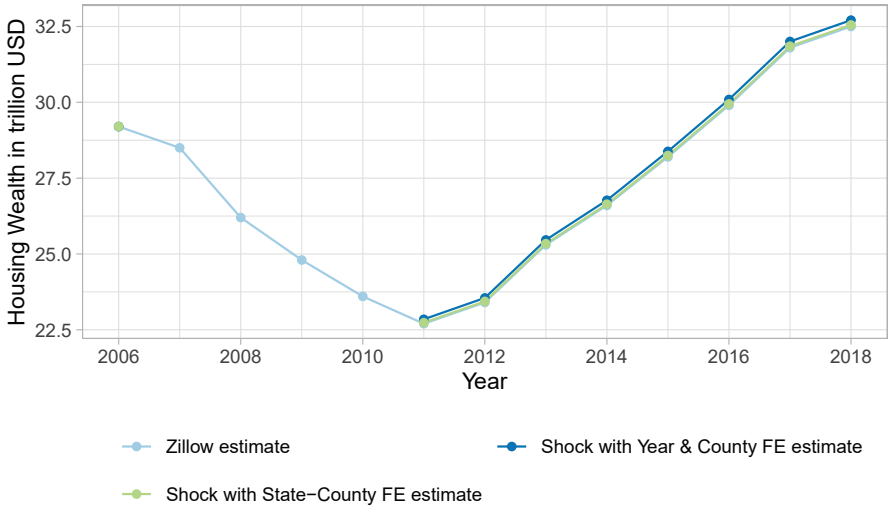


Figure 4.8. Housing wealth gap over time

We report the gap in US aggregate housing wealth by year estimated with a 21% prescription rate reduction shock in 2006 and the same housing wealth growth rate thereafter.

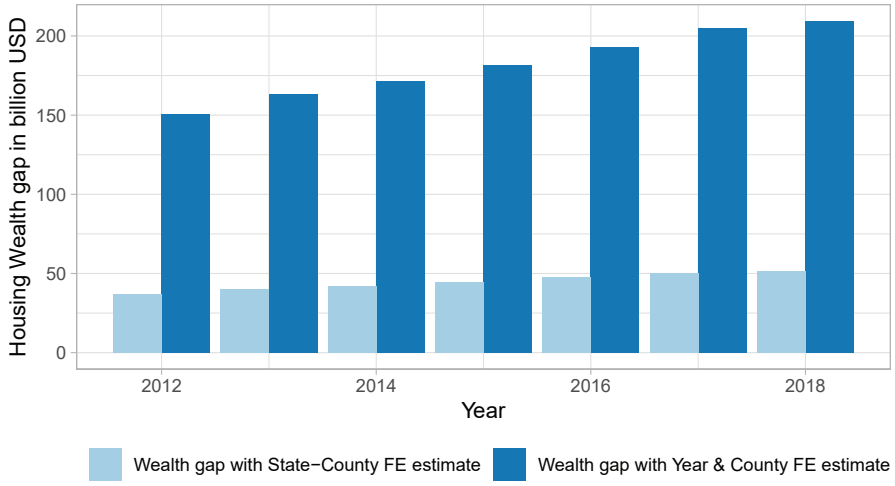
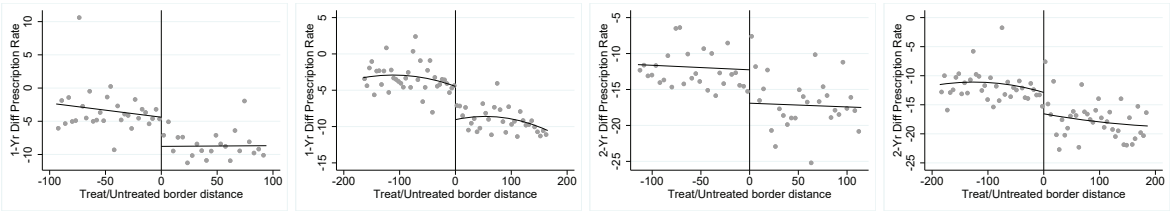


Figure 4.9. Opioid Law Impact on prescription rates around state borders: RD plots

The unit of observations are counties. We consider all counties in Panel A and all counties but counties with more than 8 pill mills in Panel B. We calculate one or two-year difference in prescription rates from the treatment year - 1 to the treatment year, respectively treatment year + 1. For control counties, we calculate the difference from 2015 to 2016 or 2017, as the first law was passed in 2016. As controls, we include the following variables as of 2015: male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth. Standard errors are clustered at the state level. The regression continuity plots correspond to Panel A in Table 4.5.

(A) All Counties



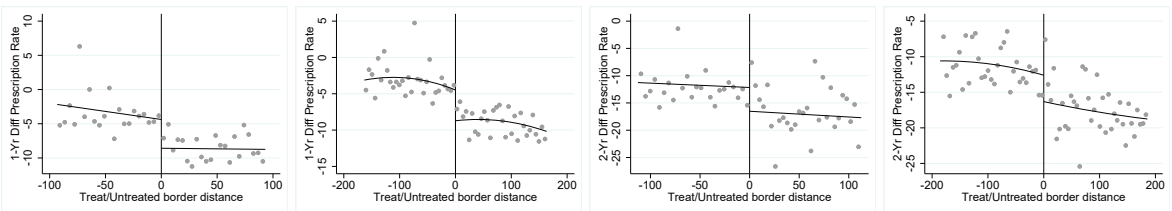
(A.1) 1-yr difference & Linear polynomial

(A.2) 1-yr difference & Quadratic polynomial

(A.3) 2-yr difference & Linear polynomial

(A.4) 2-yr difference & Quadratic polynomial

(B) Excluding counties with more than 8 pill mills



(B.1) 1-yr difference & Linear polynomial

(B.2) 1-yr difference & Quadratic polynomial

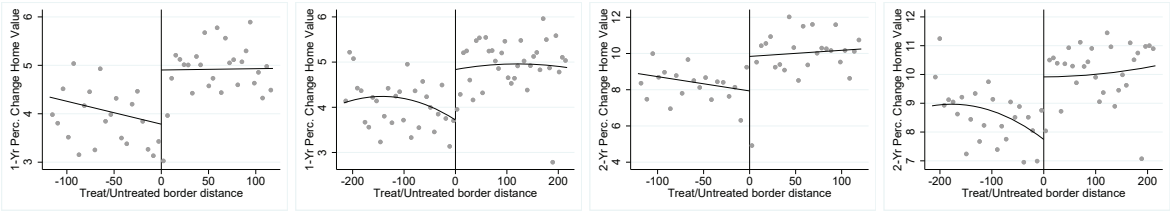
(B.3) 2-yr difference & Linear polynomial

(B.4) 2-yr difference & Quadratic polynomial

Figure 4.10. Opioid Law Impact on home values around state borders: RD plots

The unit of observations are counties. We consider all counties in Panel A and all counties but counties with more than 8 pill mills in Panel B. We calculate one or two-year percentage change in home values from the treatment year - 1 to the treatment year, respectively treatment year + 1. For control counties, we calculate the percentage change from 2015 to 2016 or 2017, as the first law was passed in 2016. As controls, we include the following variables as of 2015: male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth. Standard errors are clustered at the state level. The regression continuity plots correspond to Panel B in Table 4.5.

(A) All Counties



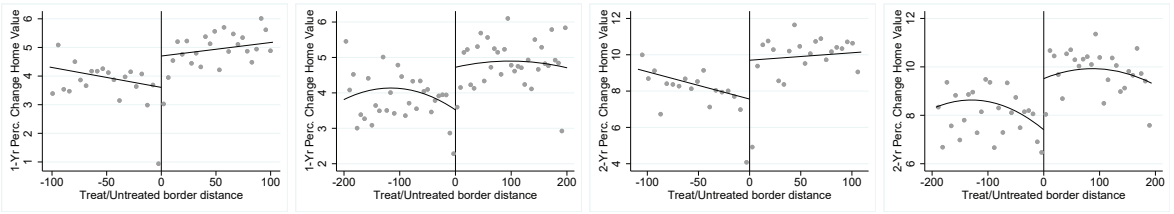
(A.1) 1-yr perc. change & Linear polynomial

(A.2) 1-yr perc. change & Quadratic polynomial

(A.3) 2-yr perc. change & Linear polynomial

(A.4) 2-yr perc. change & Quadratic polynomial

(B) Excluding counties with more than 8 pill mills



(B.1) 1-yr perc. change & Linear polynomial

(B.2) 1-yr perc. change & Quadratic polynomial

(B.3) 2-yr perc. change & Linear polynomial

(B.4) 2-yr perc. change & Quadratic polynomial

Appendix A

Green Stewards: Responsible Institutional Investors Foster Green CapEx

A.1 Investor initiatives

A.1.1 Literature approaches to identifying responsible investors

The literature has largely followed two main approaches, revealed preferences or self-declarations, to identify sustainable oriented investors. First, several papers infer preferences from investors' underlying holdings (e.g. Yang and Koci, 2020; Albuquerque, Koskinen, Yang, and Zhang, 2020; Cao, Titman, Zhan, and Zhang, 2019; Hwang, Titman, and Wang, 2022; Döttling and Kim, 2022; Gibson, Krueger, and Mitali, 2020; Kaustia and Yu, 2021; Pástor and Vorsatz, 2020; Gantchev, Giannetti, and Li, 2022). Institutional investors whose underlying holdings are more sustainable are subsequently classified as responsible. While revealed preferences avoids picking up merely window-dressing statements of investors, studying investors' portfolio responses and investor impact based on induced preferences has a circular nature. Pastor, Stambaugh, and Taylor (2023) split an institution's total AUM into its ESG and non-ESG share. While this allows to more accurately identify the overall share of ESG-aligned investing, it is not well aligned with my definition of a responsible investor. I assume that an investor has one objective across total AUM and want to study whether this translates into changes in the behavior of their portfolio companies.

Second, other papers use investors' self-declarations to identify responsible investors. Self-declarations are generally based on being a member of a sustainable investor initiative (e.g. PRI initiative by (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022; Kim and Yoon, 2023; Liang, Sun, and Teo, 2022; Dimson, Karakaş, and Li, 2021), CERES by (Flammer, 2021), CDP/CA100+ (Atta-Darkua, Glossner, Krueger, and Matos, 2022)) and therefore align investor preferences with the initiatives' objective. There has been a rapid increase in the number and size of institutional investor alliances with sustainable investment goals (see Appendix Table A.I for a list of the largest initiatives). These initiatives allow to abstract from investors' underlying holdings, but many initiatives have a relatively weak governance structure and merely

require members to sign the initiatives' objective and pay annual fees. For instance, regional "Sustainable Investment Forums" that later founded the Global Sustainable Investment Alliance (GSIA) act as platform to identify best practices and data hub. The Carbon disclosure project (CDP) gives investors access to environmental data. Other early regional networks, such as Ceres and the Institutional Investors Group on Climate Change, serve as network and launching platform for new initiatives. All of them have few if any formal requirements. The lack of formal requirements leaves ample room for greenwashing.

New initiatives have attempted to raise the bar by introducing formal requirements, but these requirements are criticized for being too loose to affect emissions. A prominent and one of the largest initiatives is the United Nations Principles for Responsible Investors (PRI) initiative. It requires signatories to report on their investment approach and in 2018 also introduced minimum requirements on portfolio and employee responsibilities. In line with greenwashing concerns, Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) show that US PRI signatories do not have better ESG ratings than non-signatories for the sample period 2013 to 2017. The most recent initiatives under the "Glasgow Financial Alliance for Net Zero" umbrella have a net-zero transition objective and formal reporting and investment requirements for signatories, but critics challenge missing requirements for divestment from fossil fuels and weak internally only based verification.[1]

A.1.2 Climate Action 100+ initiative

s The Climate Action 100+ initiative was launched in 2017 with 225 investor signatories and $26 trillion in assets under management for a period of five years. This limited period was intended in order to have a deadline for meaningful action. Over the five years, the initiative grew multifold to 700 investors with more than 68$ trillion in assets under management. In 2022 following the consultation of its signatories, the initiative

[1] Harvey, F. (2022, June 9) Bank group accused of exploiting loopholes and "greenwashing" in climate pledge'. The Guardian

Table A.I. Investor initiatives

I report a selected list of the largest investor initiatives and report the funding year in column 2, the assets under management of the initiative members as of October 2023 or latest available year in column 3, member requirements including having fees/ signing a declaration, any reporting requirements, and any requirements beyond reporting such as portfolio or engagement requirements in column 4 to 6. In column 7, I also report whether the initiative is part of a global alliance, specifically Glasgow Financial Alliance for Net Zero (GFANZ) or Global Sustainable Investment Alliance (GSIA).

(1) Initative Name	(2) Founding year	(3) AUM (in trillion USD)	(4) Fee/ declaration	(5) Reporting	(6) Active requirements	(7) Global head
UN Environment Program Finance Initiative (UNEP FI)	1992	170.0	yes	yes	yes	
Carbon disclosure project (CDP)	2000	136.0	yes	no	no	
Principles for Responsible Investment (PRI)	2005	121.3	yes	yes	yes (since 2018)	
Net-Zero Banking Alliance (NZBA)	2021	74.0	yes	yes	yes	GFANZ
Climate Action 100+ (CA100+)	2017	68.0	yes	yes	yes	
Institutional Investors Group on Climate Change (IIGCC)	2012	65.0	yes	no	no	
Ceres	1989	60.0	yes	no	no	
Net Zero Asset Managers initiative (NZAM)	2020	59.0	yes	yes	yes	GFANZ
Transition Pathway Initiative (TPI)	2017	50.0	yes	no	no	
Responsible Investment Association (Canada)	1990	42.0	yes	no	no	GSIA
Asia Investor Group on Climate Change (AIGCC)	2016	32.0	yes	no	no	
Investor Group on Climate Change (IGCC)	2005	30.0	yes	no	no	
Responsible Investment Association Australasia	1999	29.0	yes	no	no	GSIA
Coalition for Climate Resilient Investment (CCRI)	2019	28.0	yes	no	no	
European Sustainable Investment Forum (Eusosif)	2002	20.0	yes	no	no	GSIA
UK Sustainable Investment and Finance Association (UKSIF)	1991	19.0	yes	no	no	GSIA
Global Investors for Sustainable Development (GISD)	2019	16.0				
Net Zero Asset Owner's Alliance (NZAOA)	2019	11.0	yes	yes	yes	GFANZ
Net-Zero Insurance Alliance (NZIA)	2021	8.0				GFANZ
US Sustainable Investment Forum	1984	5.0	yes	no	no	GSIA
Paris Aligned Asset Owners (PAAO)	2019	3.3	yes	yes	yes	GFANZ
Net Zero Investment Consultants Initiative (NZICI)	2021	1.3				GFANZ
The Venture Climate Alliance (VCA)	2023	0.1				GFANZ
Net Zero Financial Service Providers Alliance (NZFSPA)	2021	NA				GFANZ
Japan Sustainable Investment Forum	2003	NA	yes	no	no	GSIA

was extended to 2030 to inspire a scale up in active ownership. Phase 2 marks the start of the extension and was kicked of in 2023[2]. The second phase shifted the focus from corporate climate-related disclosure to the implementation of climate transition plans. Several improvements to the transparency of the CA100+ initiative were introduced.

The objective of the initiative is to "engage with the world's largest GHG emitters to improve governance on climate change, curb emissions and strengthen climate-related financial disclosure". The collaborative engagement feature of the CA100+ initiative is one of the defining features. The initiative started out with targeting the 100 largest global emitters with engagement campaigns. It quickly extended the focus companies adding additional companies the signatories identified as critical actors in their regions' transitions or as particularly exposed to climate-related financial risks. There are currently 71 additional companies identified leading to a total of 171 focus companies with whom the initiative engages.

Engagements with a focus company are driven by one or more lead investors who can be assisted by collaborating (contributing) investors. Lead investors drive the conver-

[2] About Climate Action 100+

sation while collaborating investors support the lead investors. The investors speak for the CA100+ signatories as one voice. With the start of Phase 2 lead investors are required to set up a year-ahead engagement plan and report an annual engagement progress review. The engagement goals in line with the initiative objective are to ask companies to[3]:

- Implementing a **strong governance framework** which clearly articulates the board's accountability and oversight of climate change risk.
- Taking action to actively **reduce greenhouse gas emissions** across the value chain, including engagement with stakeholders such as policymakers and other actors to address the sectoral barriers to transition.
- Providing **enhanced corporate disclosure on and implementing transition plans** to deliver on robust targets.

There are two types of signatories, investor participants, who pursue the engagements with focus companies, and investor supporters, who are signatories to the initiative and publicly support the initiative's goals, but do not participate directly in engagements with focus companies. To become a participant signatory, the investor must be an asset owner, asset manager or a service provider that is formally representing assets and that typically conducts engagements with companies, be a member of at least one of the five socially responsible investment oriented coordinating partner organizations[4], sign the Climate Action 100+ Sign-on Statement, and purse at least one engagement with a focus company per year. All founding members were investor participants and asset owners can only sign up as investor participants. 64% of current signatories are investor participants.

[3] CA100+ press release: Climate Action 100+ Announces Its Second Phase

[4] Asia Investor Group on Climate Change (AIGCC); Ceres; Investor Group on Climate Change (IGCC); Institutional Investors Group on Climate Change (IIGCC); and Principles for Responsible Investment (PRI).

A.1.3 Identifying IMPACT-PRI investors

The United Nations Principle for Responsible Investors (PRI) initiative was launched in 2006 with 63 signatories and $6.5 trillion AUM. Since then it has grown to one of the largest initaitves on responsible investing[5]. To become a member, institutions have to sign the declaration to commit to include environmental, social and governance factors in investment decision making and ownership, pay an annual fee and complete the PRI reporting framework. Since 2018, there are also minimum sustainable portfolio and certain employee responsibility requirements. Due to its size and weaker membership requirements, there are doubts of the "true responsibility" of some of its signatories(Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022).

I therefore use the PRI survey responses from the PRI reporting framework to filter for institutional investors in this subset that similar to CA100+ follow an engagement strategy and are therefore more likely to actively care about and work on the net-zero transition. The publicly available signatory reporting data starts in 2014 and extends to 2020, translating into reporting years from 2013 to 2019[6]. New signatories have a one year grace period to submit their first report. The PRI survey includes mandatory, mandatory to answer but voluntary to disclose and voluntary questions. To identify the subset of PRI signatories that actively engage with management, I use survey questions in the "Listed Equity Active Ownership" module on the number of engagements and type of engagement[7]. 55% of signatories disclosed this information at least once. Similar to the argument for why the CA100+ is a good proxy of "real impact investors", investors who sign the declaration agreement and are willing to incur costs for actively engaging and informing their portfolio holdings about their opinion are more likely to be "real impact investors" and less likely to merely turn the portfolio

[5]For more information see: About PRI

[6]Annual reporting until 2022 takes place between January and March. In line Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) I assume that the responses correspond to the previous calendar year

[7]In 2014 to 2018, the corresponding question is LEA11.1 and LEA11.2. In 2019 and 2020, the corresponding question is LEA9.1 and LEA9.2

neutral or at worst use the PRI as green-washing instrument.

I define impact signatories as those who engage with more than 50% of their engagement targets comprehensively or signatories that engage with more than 100 companies but at least one comprehensively. I fill survey answers forward and backward if a year is missing, assuming that signatories exhibit the same engagement style if they do not disclose or have not yet submitted a survey. This adjustment allows me to have coverage for the whole time series rather the few survey years. Reassuringly, early signatories, which as mentioned are typically considered to be more serious signatories, represent a significant fraction of the IMPACT-PRI signatories, while later joiners are relatively less likely to be classified as IMPACT-PRI.

A.2 Why do firms cross-list?

A.2.1 Literature proposed and management reported reasons for cross-listing

Many different reasons for cross-listing in a foreign country have been put forward (see Karolyi (2006, 2012) for a survey of the past literature). The main theoretical reasons for cross-listing include the "market segmentation hypothesis", "bonding hypothesis", and "insulation hypothesis". Corporate managers that have successfully executed cross-listings name access to a larger and deeper market for capital, enhanced visibility, diversification of their investor base, and greater liquidity of their stock (Bancel and Mittoo, 2001, 2009; Fanto and Karmel, 1997; Mittoo, 1992) as motivation. While shareholder base diversification is one of the reasons put forward for cross-listing, neither the theoretical literature on cross-listing nor managers' stated motivation directly identify changing the proportion of sustainable oriented owners as reason.

Several surveys have directly asked managers for their motivation to cross-list. Bancel and Mittoo (2009) identify in the most recent survey of European managers enhanced visibility and the ability to raise capital as most important criteria for the choice of a foreign listing exchange. Older surveys similarly cite increased visibility, access to a deeper market for capital, greater diversification of shareholder base, enhanced stock liquidity as well as the facilitation of the implementation of a global strategy as important cross-listing benefits by managers (Bancel and Mittoo, 2001; Fanto and Karmel, 1997; Mittoo, 1992). Bancel and Mittoo (2001) also ask managers about the major consequences of a foreign listing. Disclosure of more information and the increase in the number of road shows are the most important consequences, while increasing foreign sales of developing a foreign subsidiary are not a major consequence in their sample. I manually inspect annual reports and press releases for half of my cross-listing sample to also elicit the motivation to cross-list for my sample. The results in Appendix

Table A.II column 1 echo the reason identified in the literature survey results. Access to capital and visibility are two of the most important in the cross-listing decision.

Theoretical reasons for cross-listing can be broadly framed into the following main hypotheses: ”market segmentation hypothesis”, ”bonding hypothesis”, and ”insulation hypothesis”. Again, neither talk about changes in sustainable ownership. The first theory, the market segmentation hypothesis, inspired by Stapleton and Subrahmanyam (1977); Errunza and Losq (1985); Eun and Janakiramanan (1986); Alexander, Eun, and Janakiramanan (1987) suggests that cross-listing overcomes international investment barriers that segment global investors. Firms benefit from a lower cost of capital as the firm's share become more accessible to foreign investors who would otherwise find it less advantageous to hold the shares. Stulz (1999) points out a number of challenges to the market segmentation hypothesis. First, share-price reactions to cross-listing announcements were economically small. Second, share-price reactions remained constant across time despite investment barriers becoming less significant over time. Third, share-price reactions on average between developed and emerging markets were similar even though the segmentation barriers should be different. Similarly, share-price reactions differed for firms from the same home country, while investment barriers should be similar. Finally, if the economic valuation benefits outsize the costs, all firms that would qualify for cross-listing should cross-list.

Stulz (1999) puts up the ”bonding hypothesis” as an alternative rationale for cross-listing. Weak internal governance mechanisms or home country institutions may not adequately prevent managers from extracting private benefits or controlling shareholders from expropriating private returns. Outside investors will be more hesitant to provide capital and thus increase the cost of external financing. Cross-listing is one way for firms to bond themselves to stronger governance requirements and therefore lower cost of capital. Siegel (2005) distinguishes between legal bonding and reputational bonding. Legal bonding is captured more by Coffee Jr (1999, 2002) and refers to governmental enforcement, while reputational bonding is captured more by Stulz (1999) is broader where monitoring takes place through a variety of reputational in-

termediaries, such as analysts, investment bankers, auditors and other capital market participants. Roosenboom and Van Dijk (2009) find evidence consistent with improved disclosure and the bonding hypothesis for cross-listings on US exchanges, while the evidence is mixed for continental European exchanges.

The most recent hypothesis, proposed by Kastiel and Libson (2019), suggests that cross-listing insulates firms from hostile takeovers as cross-listing increases the costs and barriers for acquirers. Launching a tender offer in both domestic and foreign exchanges can increase large direct fees as well as complexity, uncertainty and possible litigation risk. Tsang, Yang, and Zheng (2022) find empirical evidence for this conjecture.

Table A.II. Managers' motivation for cross-listing

The table summarise managers' motivations for cross-listing from the surveys from Bancel and Mittoo (2001), Fanto and Karmel (1997), and Bancel and Mittoo (2009) as well as half of the cross-listing sample of the European and Asian head-quartered firms in the USA.

	(1) My sample EU/ Asia	(2) BM2009 EU home listing	(3) BM2001 EU cross-listing	(4) BM2001 CAN cross-listing	(5) FK1997 foreign US listing	(6) FK1997 foreign ADR	(7) **Average**
Visibility	30	57	57	38	23	56	43
Capital access	38	61	38	39	23	23	37
Grow shareholder base	13	-	51	56	11	33	33
Support expansion	45	-	16	8	23	46	28
Liquidity/ stock value	9	19	11	28	-	45	22
External monitoring	-	36	-	-	-	-	36
Acquisition/ merger outcome	15	-	-	-	-	-	15
Other	2	4	-	-	-	8	5
No significant benefit	-	-	12	-	-	-	12

A.2.1.1 Evaluating responsible ownership as cross-listing driver

While the literature on cross-listing identifies several economic and market pricing efficiency reasons for cross-listings, responsible ownership has not been identified as a driver possibly because it does not matter or alternatively because it was not yet tested. I assess the importance of responsible ownership as cross-listing driver within firms, industries and countries. My results support the survey results and suggest that responsible ownership is not a key factor in managements' cross-listing decision. These findings therefore support to use cross-listing as exogenous shock for responsible ownership.

I start by documenting that the number of firms cross-listings is not related to the level or change in the origin country-level share of responsible institutional assets under management. I aggregate my data at the country-year level and restrict the sample to European and Asian countries. The dependent variable is the number of new cross-listings in a country in a given year. The key independent variable is $COUNTRY\ CA100+\ SHARE$ ($COUNTRY\ IMPACT-PRI\ SHARE$), which is the share of a country's institutional investors' assets that belong to CA100+ institutional investors (respectively IMPACT-PRI institutional investors). I consider both the country CA100+ share and the IMPACT-PRI share, as the CA100+ share is only available from 2017 onward.

I guide my choice of additional home country control variables by Sarkissian and Schill (2016)'s choice of variables that capture bonding, market pricing and economic proximity motives. I include a one-year lag of the logarithm of GDP to approximate for the economic and financial performance, a one year lag of exports to the USA relative to GDP to approximate for economic synergies to the USA, one year lag of institutional ownership, the difference between the rule of law of the home country and the USA and the difference between the financial market efficiency as measures of bonding motives, the difference in volatility between the home stock market and the US market as inverse measure of liquidity and thus pricing efficiency and the one year

lag of the share of renewable energy as measure of the degree of net zero transition of a country. GDP, volatility and rule of law data is from the World Bank, US export data is from the US Census, the renewable share from Germanwatch, and financial market efficiency is from the IMF.

My sample covers only the United States as host country and runs from 2007 to 2021. I cluster standard errors at the host country level. My dependent variable is a count of the number of cross-listing and includes many zeros. I therefore estimate the following specification with Poisson Pseudo-Maximum Likelihood:

$$\begin{aligned} Cross\text{-}Listings_{ct} =& \alpha + \beta_1 COUNTRY\ CA100 + \ SHARE_{ct-1} + \beta_2 HomeControls_{ct-1/ct} + \\ & FixedEffects + \epsilon_{ct} \end{aligned} \tag{A.1}$$

Table A.III highlights that an increase in country level responsible ownership (both CA100+ and Impact-PRI ownership) is not associated with an increase in the number of cross-listings. Regardless of controlling for region and year fixed effects or country and year fixed effects, responsible ownership does not seem to be a key driver. This results is in line with my assumption that firms list for reasons other than responsible ownership and supports its validity. In line with Sarkissian and Schill (2016), whose sample covers a longer period and multiple cross-listing host countries, I find that a countries' GDP is significantly and positively associated with new cross-listings without controlling for country fixed effects.

Next, I show that even though responsible investor pressure has increased over time, cross-listings have not tilted towards more emission intensive industries over time. If responsible investor pressure would be a key cross-listing decision factor, I would expect to see that more cross-listings originating from emission intensive industries, as these firms are most likely to be exposed to responsible investor pressure. Figure A.I plots the number of cross-listings by emission industry tercile. There is no clear observable trend of cross-listings originating more from industries in the top

Table A.III. Cross-listings drivers across and within a country

The unit of observation is country-year and the sample covers European and Asian countries. The sample period is 2016-2021 in columns 1 to 3 and 2007-2021 in columns 4 to 6. The dependent variable is the number of new cross-listings in a country and year. The key independent variable are shares of responsible institutional assets at the country based on CA100+ or IMPACT-PRI. Controls include LOGGDP, the logarithm of the home countries' GDP, EXPORTS/GDP, home countries' USA exports / GDP, COUNTRY IO SHARE, the share of the home countries' institutional ownership, DIFF(RULEOFLAW), the difference between the rule of law of the home country and the USA, DIFF(FINANCIALMARKETEFFICIENCY), the difference between the financial market efficiency of the home country and the USA, DIFF(VOLATILITY), the difference between the home countries' stock market volatility and the USA, and RENEWABLESHARE, the share of the home countries energy generated with renewable energy. The model is estimated using Poisson Pseudo-maximum likelihood. I cluster standard errors at the country level. *** 1% significance, ** 5% significance * 10% significance.

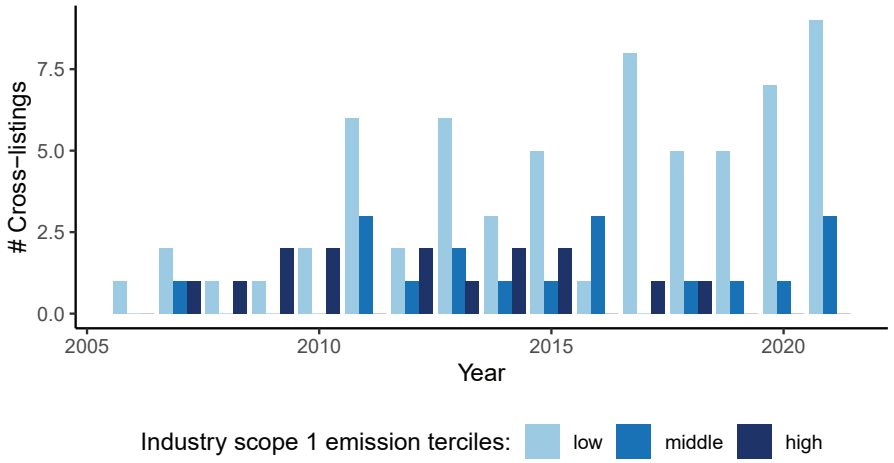
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of new cross-listings					
1YR-LAG COUNTRY CA100 SHARE	0.242	0.332	−4.777			
	(0.868)	(1.000)	(4.411)			
1YR-LAG COUNTRY IMPACT-PRI SHARE				−0.188	0.131	0.177
				(1.036)	(1.000)	(1.392)
1YR-LAG LOGGDP	0.939***	1.132***	−14.639	0.953***	1.037***	−2.013
	(0.241)	(0.251)	(14.341)	(0.163)	(0.201)	(1.316)
1YR-LAG EXPORTS/GDP	−6.225	1.549	41.312*	2.178	7.751	37.776***
	(11.680)	(8.063)	(22.917)	(7.609)	(8.918)	(13.667)
1YR-LAG COUNTRY IO SHARE	3.179	0.368	4.284	4.681**	3.378	−0.023
	(2.298)	(2.155)	(17.722)	(2.098)	(2.471)	(4.556)
DIFF(RULEOFLAW)	1.589***	1.378**	−2.913	0.748	0.522	2.596
	(0.498)	(0.613)	(7.914)	(0.565)	(0.515)	(1.657)
DIFF(FINANCIALMARKETEFFICIENCY)	0.130	0.951	−21.335	−1.214	−0.978	−2.317
	(2.736)	(1.947)	(14.607)	(1.384)	(1.218)	(2.445)
DIFF(VOLATILITY)	0.002	−0.055	0.044	−0.003	−0.034	−0.033
	(0.088)	(0.087)	(0.179)	(0.023)	(0.041)	(0.054)
1YR-LAG RENEWABLESHARE	0.005	0.009	0.014	0.001	−0.012	0.003
	(0.016)	(0.023)	(0.037)	(0.012)	(0.026)	(0.025)
Region F.E.	no	yes	no	no	yes	no
Country F.E.	no	no	yes	no	no	yes
Year F.E.	no	yes	yes	no	yes	yes
Observations	151	151	40	551	551	238
Pseudo-R2	0.363	0.399	0.217	0.282	0.313	0.257

emission-intensive tercile. In fact, if anything there seems to be a decrease in the number of cross-listings from emission-intensive industries. This observation is further suggestive evidence that responsible investor pressure is not a key decision factor in cross-listing.

Lastly, I also investigate which variables are associated with cross-listings at the firm level similar to Pagano, Röell, and Zechner (2002) and show that responsible ownership and a firms' "greenness" is not associated with cross-listing within a given industry and country. This firm-level result points also towards the change in responsible ownership being an unexpected by-product rather than a desired objective. To formally test this, I first collapse the sample of never-treated European and Asian firms and pre-treated observations of European and Asian firms at the firm level by taking

Figure A.I. Number of cross-listings and industry emissions across time

This bar plots documents the number of cross-listings per annum by emission-intensive industry tercile. I split SIC-4 industries into three terciles based on the averaged annual median scope 1 emissions between 2007 and 2021.



the average. The dependent variable is a dummy equal to one if a firm is cross-listed in the United States. The key independent variables are the CA100+ share or IMPACT-PRI share and I additionally include firm-level controls as in specification 2.2.

$$Cross\text{-}Listed_{fjc} = \alpha + \beta_1 CA100\text{-}SHARE_{fjc} + \beta_2 Controls_{fjc} + FixedEffects + \epsilon_{fjc} \tag{A.2}$$

Table A.IV documents that neither responsible ownership nor a firms' greenness is associated with the likelihood of cross-listing. As a measure of firms' greenness I consider absolute scope 1 emissions and the patent stock ratio of brown efficiency patents, i.e. patents related to fossil fuel technologies, relative to total patents. Moreover, I also do not find that the interaction of responsible ownership and firms' greenness is significantly positively related to cross-listing. Responsible ownership thus does not seem to become a more important factor for "browner" firms. Instead, I find similar to Pagano, Röell, and Zechner (2002) that larger firms and less profitable firms are more likely to cross-list in the United States.

Table A.IV. Cross-listings drivers across and within firms

I collapse the data at the firm level restricting the sample to never-treated European and Asian firms and pre-treatment observations of European and Asian firms. Columns 1 to 5 cover the sample period 2016 to 2021 and column 6 covers the period 2007 to 2021. The dependent variable is a dummy equal to one if the firm is cross-listed in the United States. The key independent variable are CA100+ SHARE or IMPACT-PRI-SHARE. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A and MSCI. All variables are averaged across the period and are defined in Table 2.11. The model is estimated using pooled regression model. All columns include country and SIC-4 industry fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cross-listed: Dummy = 1 post cross-listing					
POST-2016 CA100 SHARE	−0.003	−0.014		−0.004	−0.005	
	(0.002)	(0.009)		(0.016)	(0.004)	
POST-2016 LOGS1TOT			−0.000	0.000		
			(0.001)	(0.001)		
POST-2016 CA100 SHARE X				−0.003		
LOGS1TOT				(0.003)		
POST-2016 BROWNSTOCKRATIOWW					−0.009	
					(0.014)	
POST-2016 CA100 SHARE X					−0.016	
BROWNSTOCKRATIOWW					(0.032)	
POST-2006 IMPACT-PRI SHARE						0.001
						(0.001)
LOGSIZE	0.005***	0.007***	0.007***	0.007***	0.007***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
LOGPPE	−0.001	−0.001*	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LEVERAGE /100	0.001	0.002	0.003	0.002	0.006	0.002
	(0.004)	(0.008)	(0.008)	(0.008)	(0.005)	(0.003)
ROE /100	−0.026***	−0.055***	−0.055***	−0.055***	−0.041***	−0.021***
	(0.009)	(0.019)	(0.019)	(0.019)	(0.013)	(0.007)
M/B	−0.001*	−0.001*	−0.001*	−0.001**	−0.001	−0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
INVEST/A /100	−0.031*	−0.045	−0.047*	−0.045*	−0.061***	−0.028*
	(0.018)	(0.027)	(0.027)	(0.027)	(0.020)	(0.015)
BETA	0.008	0.073	0.072	0.073	0.011	0.013*
	(0.011)	(0.072)	(0.071)	(0.071)	(0.023)	(0.007)
VOLATILITY	0.020*	0.078*	0.075*	0.078*	0.013	0.023**
	(0.012)	(0.040)	(0.040)	(0.040)	(0.019)	(0.010)
MOM	0.019	0.059	0.051	0.057	0.046	0.024
	(0.025)	(0.065)	(0.064)	(0.065)	(0.056)	(0.019)
RETURN	−0.009*	−0.012	−0.012	−0.012	−0.010	−0.007**
	(0.005)	(0.016)	(0.016)	(0.017)	(0.011)	(0.004)
MSCI	0.000	−0.000	−0.001	0.000	−0.006	0.002
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes
Observations	19747	9984	9984	9984	12325	27411
R2	0.0678	0.125	0.125	0.125	0.103	0.0489

A.3 Appendix Tables

Table A.V. Summary statistics - CA100+ sample period

The table reports sample first quartiles, median, third quartiles, averages, standard deviations and firm-year observations for institutional ownership variables in Panel A, green debt instruments in Panel B, other green capital expenditure measures in Panel C and control variables in Panel D. The sample period is restricted to the period of the CA100+ initiative and goes from 2017 to 2022. All variables are defined in Table 2.11.

	(1) 1st Quartile	(2) Median	(3) 3rd Quartile	(4) Mean	(5) Std Dev	(6) Firm-year obs.
Panel A: Institutional ownership						
ALL INSTOSHIP	0.015	0.070	0.215	0.187	0.273	104532
CA100 SHARE	0.000	0.032	0.198	0.131	0.197	104532
PRI SHARE	0.324	0.656	0.872	0.582	0.332	104532
IMPACT-PRI SHARE	0.124	0.482	0.738	0.462	0.336	104532
Panel B: Green debt instruments						
GREENDEBT-DUMMY	0.000	0.000	0.000	0.016	0.127	104532
GREENDEBT-AMOUNT (intensive)	102.723	353.569	918.146	770.366	1387.989	1717
GREENDEBT-AMOUNT	0.000	0.000	0.000	12.654	203.012	104532
ASINH GREENDEBT-AMOUNT	0.000	0.000	0.000	0.104	0.835	104532
VERIFIED GREENDEBT-DUMMY	0.000	0.000	0.000	0.010	0.098	104532
ASINH VERIFIED GREENDEBT-AMOUNT	0.000	0.000	0.000	0.060	0.624	104532
SUSLINKDEBT-DUMMY	0.000	0.000	0.000	0.006	0.075	104532
ASINH SUSLINKDEBT-AMOUNT	0.000	0.000	0.000	0.035	0.494	104532
Panel C: Other green measures						
CLEANREVENUERATIO	0.000	0.000	0.047	0.124	0.272	7036
CLEANINVESTMENTRATIO	0.000	0.000	0.033	0.134	0.297	5902
LOGS1TOT	2.897	4.637	6.489	4.784	2.979	50534
LOGS2TOT	3.337	4.872	6.389	4.837	2.371	50581
LOGS3UPTOT	5.145	6.661	8.115	6.608	2.279	50595
S1INT	0.060	0.163	0.445	1.821	5.544	50595
S2INT	0.085	0.191	0.426	0.402	0.578	50595
S3UPINT	0.486	1.082	2.286	1.681	1.651	50595
GREENRATIOEP	0.000	0.000	0.143	0.144	0.281	11988
GREENRATIOWW	0.000	0.000	0.059	0.079	0.186	36692
GREENCITCOUNTEP	0.000	0.000	1.000	45.358	2253.759	11988
GREENCITCOUNTWW	0.000	0.000	1.000	45.146	1398.498	36692
GREENCITMAXEP	0.000	0.000	1.000	30.385	2232.183	11988
GREENCITMAXWW	0.000	0.000	1.000	17.541	1291.725	36692
Panel D: Control variables						
LOGSIZE	4.793	6.041	7.387	6.137	1.965	104532
LEVERAGE	4.430	17.956	33.784	21.406	18.841	104532
ROE	0.224	7.391	14.295	0.401	32.798	104532
INVEST/A	0.726	2.498	5.519	4.091	4.887	104532
M/B	0.875	1.590	3.139	2.643	2.937	104532
BETA	0.741	0.944	1.138	0.932	0.463	104532
VOLAT	0.066	0.098	0.147	0.123	0.101	104532
MOM	−0.019	0.002	0.024	0.003	0.043	104532
RET	−0.058	0.000	0.056	0.008	0.137	104532
MSCI	0.000	0.000	0.000	0.165	0.371	104532

Table A.VI. Green debt & emissions

The unit of observation is firm-year. The sample period is 2013-2022. The dependent variable is $LOGS1TOT$, in columns 1 and 2, $S1INT$ in columns 3 and 4, $LOGS123UPTOT$, in columns 5 and 6 and $S123UPINT$ in columns 7 and 8. In Panel A, the sample includes all firms and in Panel B is restricted to non-finance firms. The key independent variable is $GREENDEBT-DUMMY$. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All columns include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LOGS1TOT		S1INT		LOGS123UPTOT		S123UPINT	
Panel A: Full sample								
1YR-LAG GREENDEBT-DUMMY	−0.027		−0.217**		−0.046***		−0.276***	
	(0.032)		(0.086)		(0.017)		(0.102)	
3YR-LAG GREENDEBT-DUMMY		−0.068		−0.144		−0.047**		−0.180
		(0.042)		(0.097)		(0.021)		(0.113)
Observations	80866	65267	80969	65340	80969	65340	80969	65340
R2	0.959	0.961	0.938	0.941	0.975	0.975	0.942	0.945
Panel B: Without finance industry								
1YR-LAG GREENDEBT-DUMMY	−0.034		−0.303**		−0.030		−0.362**	
	(0.034)		(0.130)		(0.019)		(0.155)	
3YR-LAG GREENDEBT-DUMMY		−0.094*		−0.228		−0.044*		−0.286*
		(0.050)		(0.151)		(0.027)		(0.174)
Observations	67208	54427	67260	54463	67260	54463	67260	54463
R2	0.958	0.959	0.938	0.941	0.976	0.976	0.941	0.944
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes

Table A.VII. Additional alternative responsible ownership measures & green debt

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. The key independent variables are $CA100-PARTICIPANT\ SHARE$ in Panel A, $CA100\ W/O\ HIGH-EMISSION-INTENSITY\ SHARE$ in Panel B and $CA100\ W.NBIM\ SHARE$ in Panel C. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
Panel A: CA100+ Participants only								
1YR-LAG CA100-PARTICIPANT	0.018***		0.018***		0.108***		0.106***	
SHARE	(0.002)		(0.003)		(0.016)		(0.017)	
3YR-LAG CA100-PARTICIPANT		0.033***		0.043***		0.217***		0.277***
SHARE		(0.006)		(0.007)		(0.037)		(0.045)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0885	0.115	0.456	0.583
Panel B: Without high emission intensity investors								
1YR-LAG CA100 W/O	0.021***		0.023***		0.137***		0.141***	
HIGH-EMISSION INTENSITY SHARE	(0.003)		(0.003)		(0.019)		(0.021)	
3YR-LAG CA100 W/O		0.026***		0.042***		0.206***		0.287***
HIGH-EMISSION INTENSITY SHARE		(0.007)		(0.008)		(0.046)		(0.053)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0886	0.115	0.456	0.583
Panel C: CA100+ with Norges Bank Investment Management from start								
1YR-LAG CA100 W. NBIM SHARE	0.016***		0.018***		0.101***		0.106***	
	(0.002)		(0.003)		(0.013)		(0.015)	
3YR-LAG CA100 W. NBIM SHARE		0.024***		0.032***		0.159***		0.209***
		(0.004)		(0.006)		(0.028)		(0.037)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0860	0.111	0.445	0.568	0.0886	0.115	0.456	0.583
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.VIII. 4/5 Responsible ownership measures & green debt

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. For the key independent variables are $CA100\ SHARE-1/5\ DROP$, I randomly allocate all signatories into 5 equally sized buckets and iteratively drop one signatory bucket. The $CA100\ SHARE-1/5\ DROP$ is thus based on 4/5 of all signatories. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include industry-year and firm fixed effects. Impact signatories are signatories who report in the survey that they engage with more than 50% of their engagement targets comprehensively or signatories that engage with more than 100 companies but at least one comprehensively. The question is mandatory to answer, but voluntary to disclose. I fill survey answers forward and backward if a year is missing. First survey data is from 2013 and last from 2019. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
Panel A: CA100 share without signatory bucket one								
1YR-LAG CA100 SHARE-1/5 DROP (V1)	0.016*** (0.003)		0.018*** (0.003)		0.102*** (0.016)		0.111*** (0.017)	
3YR-LAG CA100 SHARE-1/5 DROP (V1)		0.026*** (0.006)		0.038*** (0.007)		0.179*** (0.037)		0.243*** (0.045)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0858	0.111	0.445	0.568	0.0885	0.115	0.456	0.583
Panel B: CA100 share without signatory bucket two								
1YR-LAG CA100 SHARE-1/5 DROP (V2)	0.009*** (0.003)		0.007** (0.003)		0.058*** (0.017)		0.038** (0.018)	
3YR-LAG CA100 SHARE-1/5 DROP (V2)		0.036*** (0.007)		0.047*** (0.008)		0.233*** (0.042)		0.301*** (0.052)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0856	0.111	0.445	0.568	0.0882	0.115	0.455	0.583
Panel C: CA100 share without signatory bucket three								
1YR-LAG CA100 SHARE-1/5 DROP (V3)	0.020*** (0.003)		0.018*** (0.003)		0.121*** (0.016)		0.108*** (0.019)	
3YR-LAG CA100 SHARE-1/5 DROP (V3)		0.038*** (0.007)		0.041*** (0.008)		0.246*** (0.041)		0.262*** (0.051)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0860	0.111	0.445	0.568	0.0886	0.115	0.456	0.583
Panel D: CA100 share without signatory bucket four								
1YR-LAG CA100 SHARE-1/5 DROP (V4)	0.020*** (0.003)		0.021*** (0.003)		0.116*** (0.016)		0.125*** (0.019)	
3YR-LAG CA100 SHARE-1/5 DROP (V4)		0.029*** (0.007)		0.039*** (0.008)		0.188*** (0.041)		0.258*** (0.050)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0885	0.115	0.456	0.583
Panel E: CA100 share without signatory bucket five								
1YR-LAG CA100 SHARE-1/5 DROP (V5)	0.020*** (0.003)		0.021*** (0.003)		0.123*** (0.018)		0.130*** (0.019)	
3YR-LAG CA100 SHARE-1/5 DROP (V5)		0.029*** (0.006)		0.042*** (0.008)		0.187*** (0.039)		0.267*** (0.048)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0859	0.111	0.445	0.568	0.0886	0.115	0.456	0.583
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.IX. CA100+ share & green debt with alternative specification

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. In Panel A, the key independent variable is $CA100\ SHARE$, but the sample is restricted to firms with at least 10% institutional ownership. In Panel B the key independent variable is $CA100\ INSTOSHIP$, which is the CA100+ share relative to all owners. I also include $ALL\ INSTOSHIP$, which is the total proportion of all institutional investors as additional control. In Panel C, the key independent variables are dummies for different proportions of $CA100\ SHARE$. The omitted group is firms with responsible ownership below 10%. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
Panel A: Restricting the sample to firms with at least 10% institutional ownership								
1YR-LAG CA100 SHARE	0.037***		0.039***		0.212***		0.213***	
	(0.008)		(0.011)		(0.049)		(0.068)	
3YR-LAG CA100 SHARE		0.050***		0.106***		0.322***		0.688***
		(0.015)		(0.023)		(0.096)		(0.144)
Observations	42061	22175	40587	20713	42061	22175	40587	20713
R2	0.1	0.2	0.5	0.6	0.1	0.2	0.5	0.6
Panel B: CA100+ ownership relative to all owners								
1YR-LAG CA100 INSTOSHIP	0.129***		0.105***		0.932***		0.777***	
	(0.015)		(0.015)		(0.102)		(0.105)	
1YR-LAG ALL INSTOSHIP	−0.038***		−0.023***		−0.264***		−0.157***	
	(0.003)		(0.007)		(0.022)		(0.046)	
3YR-LAG CA100 INSTOSHIP		0.286***		0.265***		2.098***		1.890***
		(0.043)		(0.054)		(0.295)		(0.364)
3YR-LAG ALL INSTOSHIP		−0.043***		−0.024		−0.292***		−0.099
		(0.005)		(0.018)		(0.034)		(0.111)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.1	0.1	0.4	0.6	0.1	0.1	0.5	0.6
Panel C: CA100+ proportion indicators								
1YR-LAG DCA100SHARE 10%-30%	0.001		0.002*		−0.003		0.012	
	(0.001)		(0.001)		(0.008)		(0.008)	
1YR-LAG DCA100SHARE 30%+	0.017***		0.015***		0.107***		0.096***	
	(0.002)		(0.002)		(0.011)		(0.012)	
3YR-LAG DCA100SHARE 10%-30%		0.019***		0.016***		0.122***		0.101***
		(0.003)		(0.003)		(0.018)		(0.018)
3YR-LAG DCA100SHARE 30%+		0.017***		0.019***		0.111***		0.115***
		(0.004)		(0.005)		(0.026)		(0.029)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.1	0.1	0.4	0.6	0.1	0.1	0.5	0.6
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.X. CA100+ share & other green bond measures

The unit of observation is firm-year. The sample period is 2017-2022. In Panel A, the dependent variable is $VERIFIED\ GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(VERIFIED\ GREENDEBT)$ in columns 5 to 8. In Panel B, the dependent variable is $SUSLINKBOND-DUMMY$ in columns 1 to 4 and $ASINH(SUSLINKBOND)$ in columns 5 to 8.$CA100\ SHARE$ is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Green bonds	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	VERIFIED GREENDEBT-DUMMY				ASINH(VERIFIED GREENDEBT)			
1YR-LAG CA100 SHARE	0.010***		0.008***		0.057***		0.044***	
	(0.002)		(0.002)		(0.012)		(0.013)	
3YR-LAG CA100 SHARE		0.019***		0.026***		0.119***		0.153***
		(0.005)		(0.006)		(0.029)		(0.034)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0652	0.0847	0.437	0.553	0.0670	0.0875	0.461	0.583
Panel B: Sustainability-linked bonds								
	SUSLINKDEBT-DUMMY				ASINH(SUSLINKBOND)			
1YR-LAG CA100 SHARE	0.006***		0.007***		0.042***		0.048***	
	(0.001)		(0.002)		(0.009)		(0.010)	
3YR-LAG CA100 SHARE		0.012***		0.018***		0.089***		0.132***
		(0.003)		(0.005)		(0.021)		(0.031)
Observations	104460	55206	104460	55206	104460	55206	104460	55206
R2	0.0399	0.0533	0.343	0.473	0.0410	0.0552	0.340	0.475
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.XI. CA100+ share & green debt w/o financial institutions

The unit of observation is firm-year. The sample period is 2017-2022 and the sample is restricted to non-financial institutions. The dependent variable is $GREENDEBT-DUMMY$ in columns 1 to 4 and $ASINH(GREENDEBT)$ in columns 5 to 8. The key independent variable is $CA100\ SHARE$. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENDEBT-DUMMY				ASINH(GREENDEBT)			
1YR-LAG CA100 SHARE	0.015***		0.018***		0.091***		0.106***	
	(0.002)		(0.003)		(0.014)		(0.016)	
3YR-LAG CA100 SHARE		0.022***		0.025***		0.140***		0.171***
		(0.005)		(0.007)		(0.032)		(0.042)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	no	no	yes	yes	no	no
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	no	no	yes	yes	no	no
Ind-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes
Observations	87499	46251	87499	46251	87499	46251	87499	46251
R2	0.0767	0.0994	0.418	0.541	0.0781	0.102	0.426	0.556

Table A.XII. CA100+ share & alternative green innovation measures

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is *GREENCITMAXWW* in columns 1 to 4 and *GREENCITMAXEP* in columns 5 to 8 in Panel A, respectively *GREENCITCOUNTWW* in columns 1 to 4 and *GREENCITCOUNTEP* in columns 5 to 8 in Panel B. *CA*100 *SHARE* is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Worldwide green innovation								
	GREENRATIOWW				GREENCITCOUNTWW			
1YR-LAG CA100 SHARE	0.169		0.244**		−0.866		−0.195	
	(0.104)		(0.110)		(1.091)		(0.883)	
3YR-LAG CA100 SHARE		−0.015		0.291		3.116***		0.185
		(0.221)		(0.311)		(1.198)		(2.072)
Observations	36522	16800	20437	7808	35848	16012	15284	4728
Pseudo R2	0.115	0.113	0.249	0.236	0.651	0.641	0.921	0.937
Panel B: Maximum citations of green patents								
	GREENCITMAXEP				GREENCITMAXWW			
1YR-LAG CA100 SHARE	5.067**		7.141***		−0.691		0.022	
	(2.204)		(2.526)		(1.663)		(1.297)	
3YR-LAG CA100 SHARE		5.747***		10.030**		3.530***		−0.859
		(1.520)		(4.743)		(1.018)		(2.247)
Observations	11370	4510	4664	1190	35848	16012	15284	4728
Pseudo R2	0.827	0.605	0.969	0.938	0.671	0.648	0.943	0.933
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.XIII. CA100+ share & scope 3 emissions

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is *LOGS3UPTOT* in columns 1 to 4 and *S3UPINT* in columns 5 to 8. *CA*100 *SHARE* is the key independent variables. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. Columns 1, 2, 5 and 6 include year, country, and SIC-4 industry fixed effects. Columns 3,4, 7 and 8 include year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LOGS3UPTOT				S3UPINT			
1YR-LAG CA100 SHARE	0.038		−0.017		−0.005		−0.000	
	(0.057)		(0.025)		(0.047)		(0.018)	
3YR-LAG CA100 SHARE		0.164		0.038		0.116		0.022
		(0.127)		(0.057)		(0.094)		(0.021)
Observations	50754	24940	49726	23627	50754	24940	49726	23627
R2	0.817	0.799	0.982	0.991	0.730	0.733	0.983	0.995
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes

Table A.XIV. Roth (2022) pre-test

I follow Roth (2022) to identify whether my pre-test is likely to be well powered against violations of parallel trends. For the dependent variables $AMERICAN\,SHARE$, $CA100\,SHARE$, $IMPACT-PRI\,SHARE$, $GREENDEBT-DUMMY$, $ASINH(GREENDEBT)$ and $LOSG1TOT$, I back out the slope to have an estimated power of 0.5. I report the slope, power (probability that no significant pre-period coefficient would be detected under the hypothesized trend), the Bayes Factor (relative probability that no significant pre-period coefficient would be detected under the hypothesized trend relative to under parallel trends) and the likelihood ratio (the relative likelihood of the estimated coefficients under the hypothesized trend relative to under parallel trends)

	(1) Slope	(2) Power	(3) Bayes Factor	(4) Likelihood Ratio
US SHARE	0.016	0.500	0.571	0.024
CA100 SHARE	-0.039	0.501	0.558	1.079
IMPACT-PRI SHARE	-0.016	0.500	0.561	0.139
GREENDEBT-DUMMY	-0.003	0.499	0.572	1.564
ASINH(GREENDEBT-AMOUNT)	-0.024	0.500	0.571	1.183
LOGSCOPE1TOT	0.091	0.500	0.575	0.591

Table A.XV. Responsible investor impact on scope 1 emissions of investor target firms

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is $LOGS1TOT$ in columns 1 to 4 and $S1INT$ in columns 5 to 8. The key independent variables are $CA100\,SHARE$ and its interaction with $HIGHESTEMITTERS$, a dummy equal to one for the for firms in the top 200 highest emitters in 2016 by total scope 1 emissions, as well as its interaction with $CA100TARGET$, a dummy equal to one if the firm is part of the target company set of the CA100+ initiative. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LOGS1TOT				S1INT			
1YR-LAG CA100 SHARE	−0.116***	−0.118***			−0.021	−0.043		
	(0.044)	(0.044)			(0.102)	(0.103)		
1YR-LAG CA100 SHARE X	−0.533*				−3.898**			
HIGHEST EMITTERS	(0.293)				(1.564)			
1YR-LAG CA100 SHARE X		−0.591***				−3.113***		
CA100 TARGET		(0.183)				(1.027)		
3YR-LAG CA100 SHARE			−0.161*	−0.160*			−0.207*	−0.240*
			(0.090)	(0.090)			(0.122)	(0.124)
3YR-LAG CA100 SHARE X			−0.485				−7.771***	
HIGHEST EMITTERS			(0.382)				(2.274)	
3YR-LAG CA100 SHARE X				−0.730**				−3.432**
CA100 TARGET				(0.340)				(1.490)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Observations	49666	49666	23583	23583	49726	49726	23627	23627
R2	0.971	0.971	0.985	0.985	0.956	0.956	0.978	0.978

Table A.XVI. Responsible investor impact on firm size

The unit of observation is firm-year. The sample period is 2017-2022. The dependent variable is *LOGASSETS* in columns 1 to 4 and *LOGSALES* in columns 5 to 8. The key independent variables are *CA*100 *SHARE*. In Panel B, I additional interact the *CA*100 *SHARE* with *HIGHESTEMITTERS*, a dummy equal to one for the for firms in the top 200 highest emitters in 2016 by total scope 1 emissions, and *CA*100*TARGET*, a dummy equal to one if the firm is part of the target company set of the CA100+ initiative. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. All variables are defined in Table 2.11. All independent variables are lagged by one or three years. The model is estimated using pooled regression model. All regressions include industry-year and firm fixed effects. I cluster standard errors at the firm level. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Full sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LOGASSETS				LOGSALES			
1YR-LAG CA100 SHARE	0.005		−0.035***		0.010		−0.059***	
	(0.016)		(0.009)		(0.028)		(0.013)	
3YR-LAG CA100 SHARE		−0.033		−0.078***		0.014		−0.088***
		(0.036)		(0.015)		(0.056)		(0.024)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	no	no	yes	yes	no	no
Country F.E.	yes	yes	no	no	yes	yes	no	no
Industry F.E.	yes	yes	no	no	yes	yes	no	no
Ind-Year F.E.	no	no	yes	yes	no	no	yes	yes
Firm F.E.	no	no	yes	yes	no	no	yes	yes
Observations	104460	55206	104460	55206	104459	55206	104459	55206
R2	0.931	0.913	0.991	0.996	0.845	0.828	0.983	0.992

Panel B: Investor target firms interaction								
	LOGASSETS				LOGSALES			
1YR-LAG CA100 SHARE	−0.035***	−0.035***			−0.060***	−0.060***		
	(0.009)	(0.009)			(0.014)	(0.014)		
1YR-LAG CA100 SHARE X	0.030				0.128			
HIGHEST EMITTERS	(0.059)				(0.089)			
1YR-LAG CA100 SHARE X		0.039				0.082		
CA100 TARGET		(0.072)				(0.103)		
3YR-LAG CA100 SHARE			−0.078***	−0.078***			−0.089***	−0.089***
			(0.015)	(0.015)			(0.024)	(0.024)
3YR-LAG CA100 SHARE X			−0.075				0.254**	
HIGHEST EMITTERS			(0.115)				(0.127)	
3YR-LAG CA100 SHARE X				−0.046				0.251
CA100 TARGET				(0.150)				(0.165)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Ind-Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104460	104460	55206	55206	104459	104459	55206	55206
R2	0.991	0.991	0.996	0.996	0.983	0.983	0.992	0.992

A.4 Appendix Figures

Figure A.II. Green Debt Matching

The sample is 2013 to 2022. I report the total number of green debt issuances by public firms in Bloomberg by non-matched (grey), matched - not in sample (light blue) and matched - in sample (blue) per year.

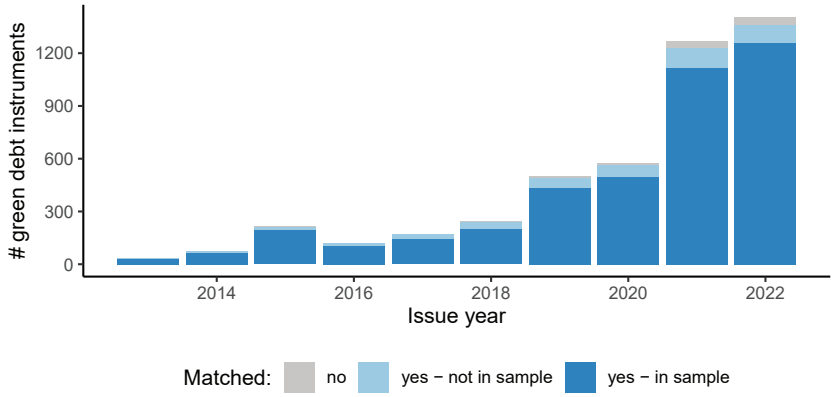
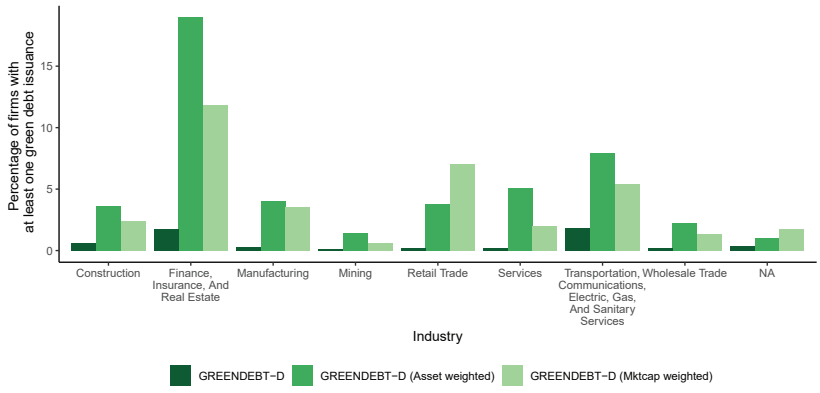
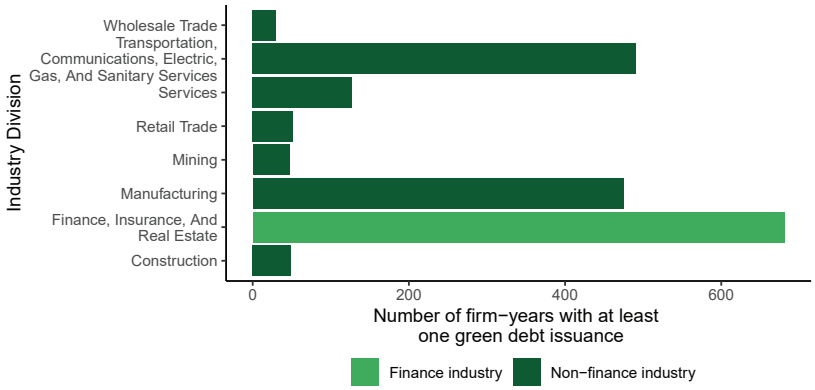


Figure A.III. Green Debt Issuance By Industry

The sample is 2013 to 2022. I report the proportion of firm-years with at least one green debt issuance by SIC major division in Panel A and the number of firm-year observations with at least one green debt issuance by SIC major division in Panel B.



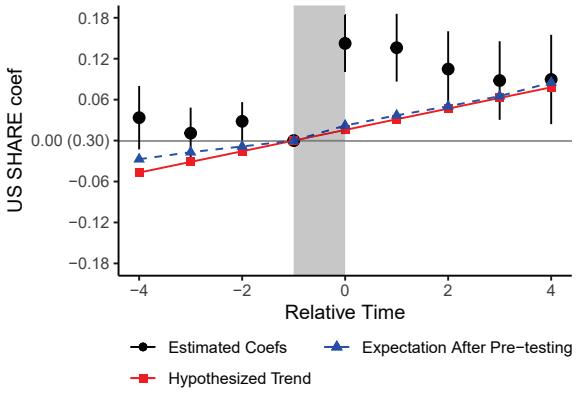
(a) Green debt issuance proportion by industry division



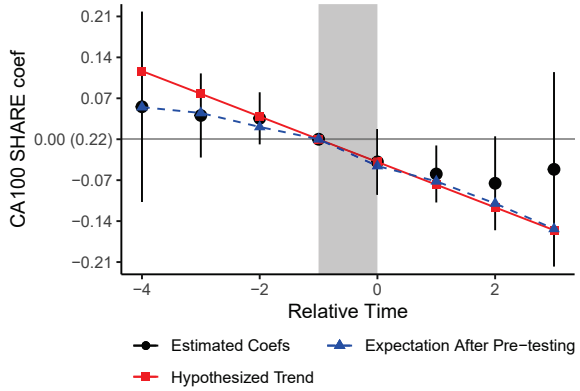
(b) Firm-year observations with green debt issuance by industry division

Figure A.IV. Cross-Listing in the United States and Institutional Ownership - Roth Pretrends

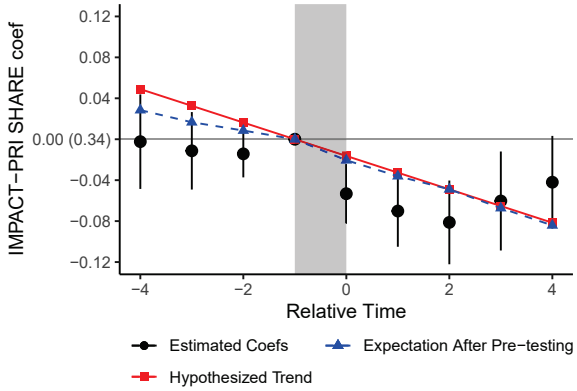
The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2014 to 2021. The dependent variable is the AMERICAN SHARE in Panel A, CA100 SHARE in Panel B and IMPACT-PRI SHARE in Panel C. I follow Roth (2022) and plot a linear violation of the pre trend based on a 50% power in red. Black are coefficients we find in our regression and blue are the expected coefficient we would find based on the hypothesized trend in red.



(a) AMERICAN SHARE



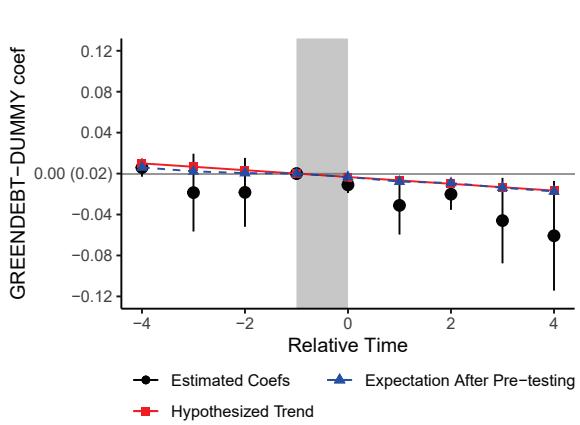
(b) CA100 SHARE



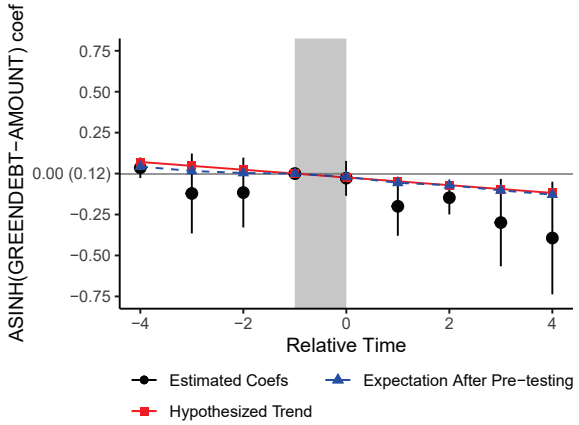
(c) IMPACT-PRI SHARE

Figure A.V. Cross-Listing in the United States and Green Capex - Roth Pretrends

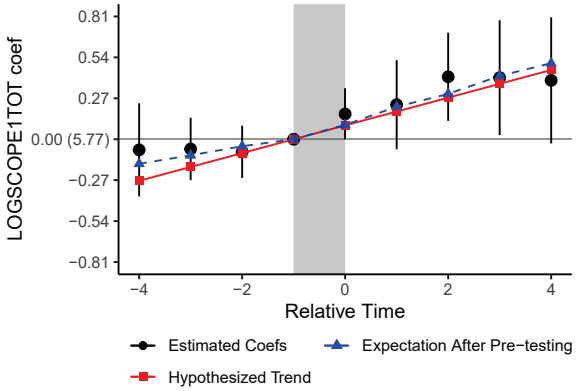
The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2014 to 2021 in Panel A and B, respectively 2007 to 2021 in Panel C. The dependent variable is GREENDEBT-DUMMY in Panel A, ASINH(GREENDEBT) in Panel B, and LOGS1TOT in Panel C. I follow Roth (2022) and plot a linear violation of the pre trend based on a 50% power in red. Black are coefficients we find in our regression and blue are the expected coefficient we would find based on the hypothesized trend in red.



(a) GREENDEBT-DUMMY



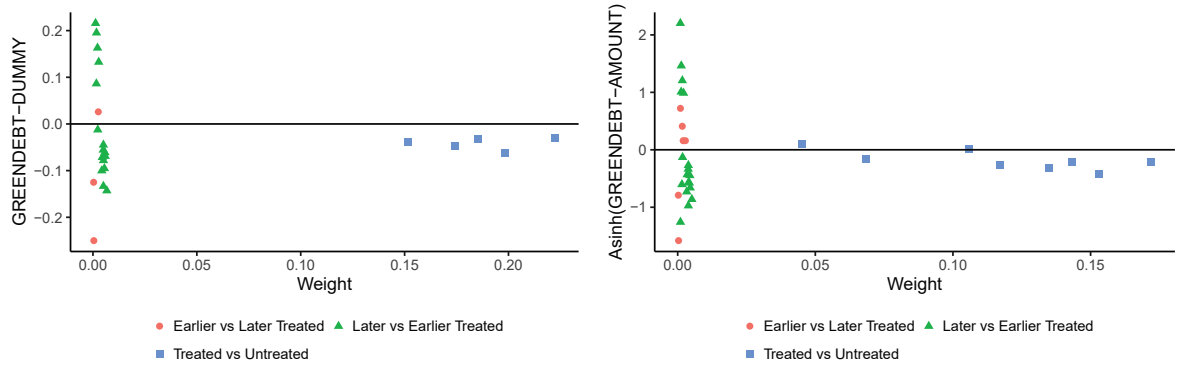
(b) ASINH(GREENDEBT)



(c) LOGS1TOT

Figure A.VI. Cross-Listing in the United States and Green Debt - Bacon decomposition w/o controls

The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2014 to 2021. The dependent variable is GREENDEBT-DUMMY in Panel A and ASINH(GREENDEBT) in Panel B. I show the Goodman-Bacon (2021) decompositions for the TWFE regression without any controls.



(a) GREENDEBT-DUMMY **(b)** ASINH(GREENDEBT)

Figure A.VII. Cross-Listing in the United States and scope 1 emission intensity

The unit of observation is firm-year. The sample is the matched US cross-listing sample between 2007 to 2021. The dependent variable is S1INT. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.

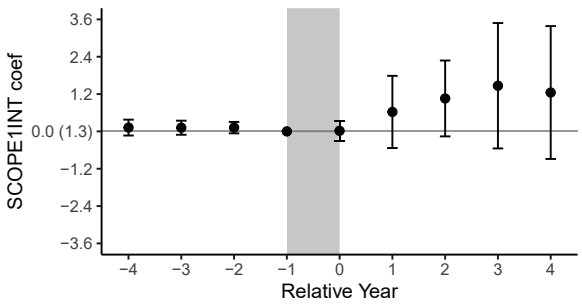
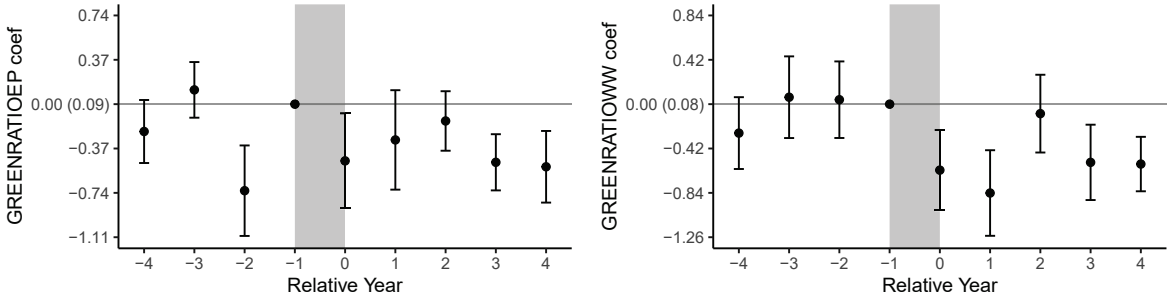


Figure A.VIII. Cross-Listing in the United States and Green Innovation

The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2007 to 2021. The dependent variable is GREENRATIOEP in Panel A and GREENRATIOWW in Panel B. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. The model is estimated using Poisson pseudo-maximum likelihood and I calculate interaction weighted total coefficients with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) GREENRATIOEP **(b)** GREENRATIOWW

Figure A.IX. Cross-Listing in the United States and Foreign Sales Percentage

The unit of observation is firm-year. The sample is the matched US cross-listing sample between 2007 to 2021. The dependent variable is PERCTFORSALES. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.

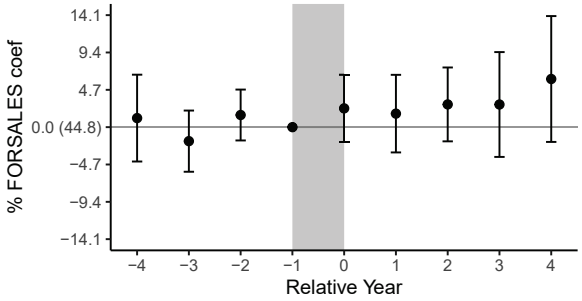
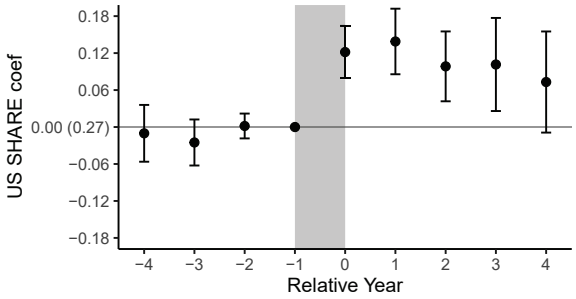
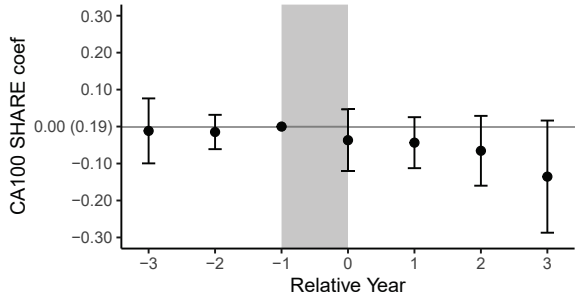


Figure A.X. European Firms' Cross-Listing in the United States and Sustainable Ownership

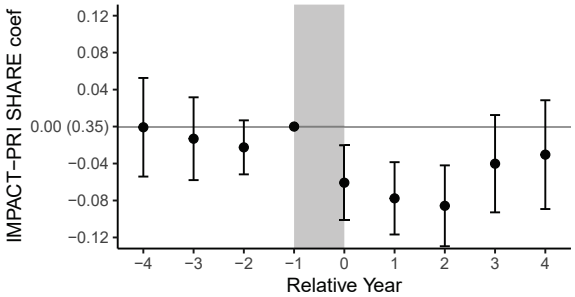
The unit of observation is firm-year. The sample is the matched sample of European headquartered firms that cross-listed in the United States between 2007 to 2021, except for Panel B where it is between 2017 to 2021. The dependent variable is the American SHARE, the share of American institutional ownership relative to total institutional ownership, in Panel A, CA100 SHARE in Panel B and IMPACT PRI SHARE in Panel C. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) AMERICAN SHARE



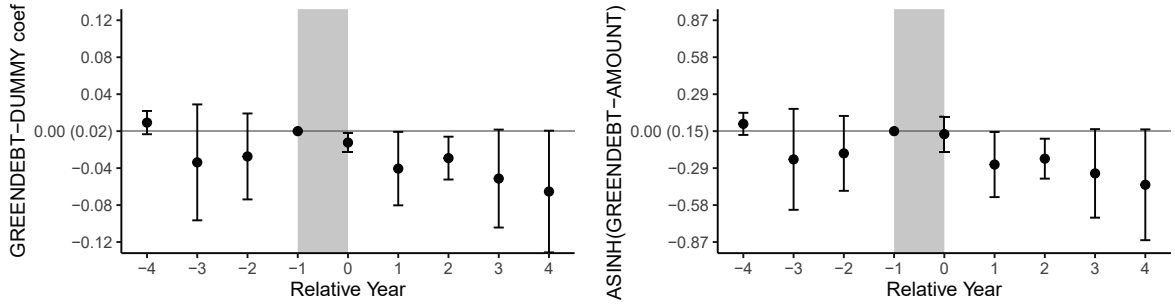
(b) CA100+ SHARE



(c) Impact-PRI SHARE

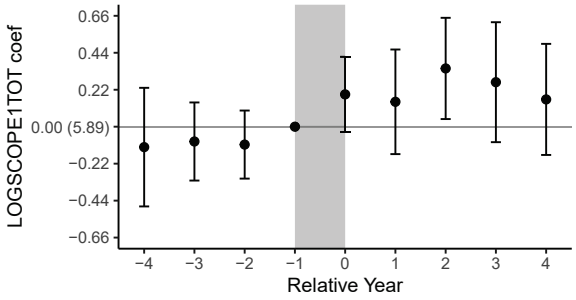
Figure A.XI. European Firms' Cross-Listing in the United States and Green CapEx

The unit of observation is firm-year. The sample is the matched sample of Asian and European headquartered firms that cross-listed in the United States between 2014 to 2021 in Panel A and B, respectively 2007 to 2021 in Panel C. The dependent variable is GREENDEBT-DUMMY in Panel A, ASINH(GREENDEBT) in Panel B, and LOGS1TOT in Panel C. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) GREENDEBT-DUMMY

(b) ASINH(GREENDEBT)



(c) LOGS1TOT

Figure A.XII. American Firms Cross-Listing in Europe

The sample is 2007 to 2021. I report the number of American firms that cross-listed in a given year and are part of the final difference-in-difference sample.

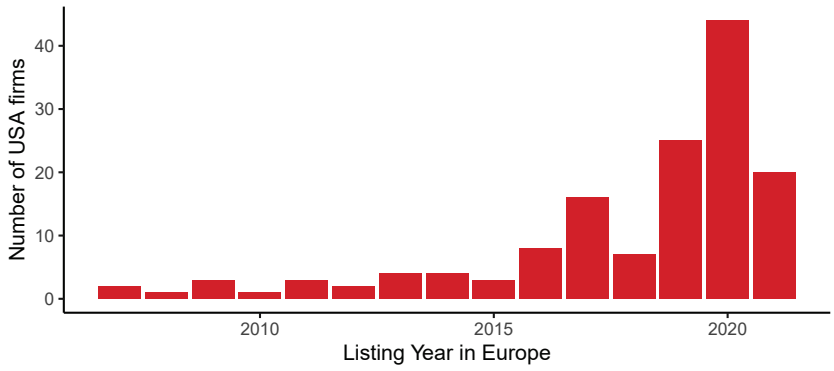
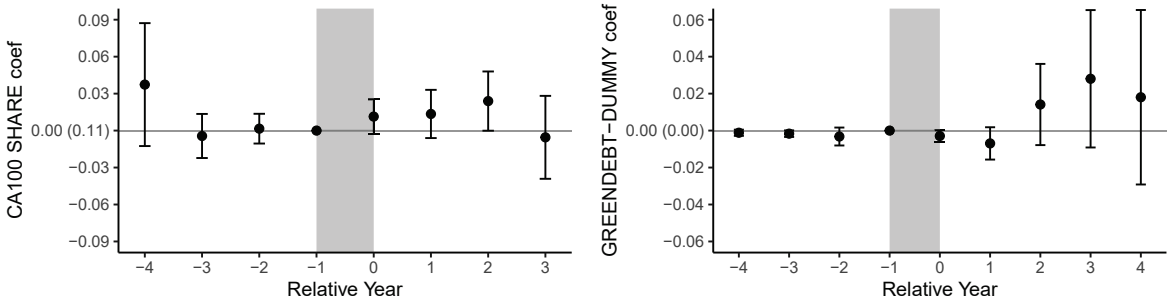


Figure A.XIII. Impact on American Firms Cross-Listing in Europe

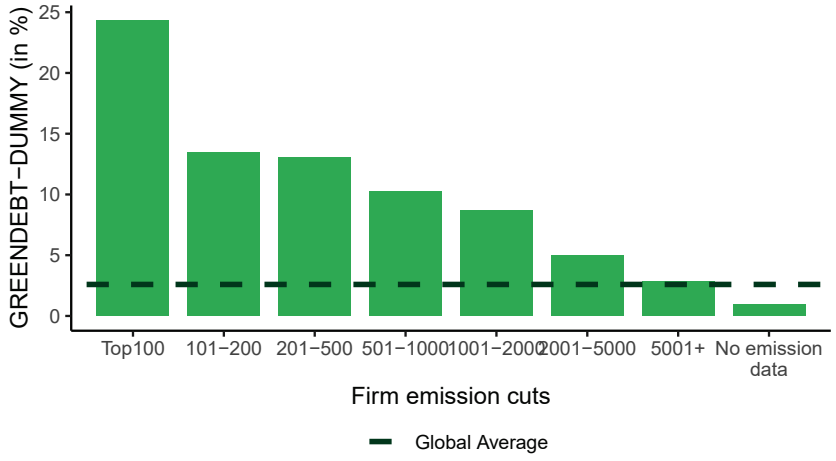
The unit of observation is firm-year. The sample is the US-firm matched European cross-listing sample between 2014 to 2021. The dependent variable is CA100 SHARE in Panel A and GREENDEBT-D in Panel B. Controls include LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, BETA, VOLAT, MOM, RET, INVEST/A, MSCI. I plot the interaction weighted total coefficient with a 90% confidence interval for each relative time period following Sun and Abraham (2021b). I cluster standard errors at the firm level.



(a) CA100 SHARE **(b)** GREENDEBT-DUMMY

Figure A.XIV. Proportion of firms with green debt by emitter subsets

The sample is 2020 to 2021. I report the average proportion of firm-years with at least one green debt issuance for the highest 100 emitters in 2016 and firm emission cuts thereafter.



A.5 Extension of Pástor, Stambaugh, and Taylor (2021) with investor engagement

Pástor, Stambaugh, and Taylor (2021) analyze amongst others how changes in agents' preferences for sustainability can have real social impact on society. They study how firms respond to asset pricing effects with investor preferences for ESG characteristics. They assume that managers maximize the firm's market value and show that sustainable investing produces positive social impact by making firms greener and by shifting real investment toward green firms. I extend the model by altering the assumption of firm market value maximization. Instead, I assume that management compensation is linked to both firm value and social impact. The larger the share of institutional investors, the larger the fraction of compensation linked to social impact. This models one possible channel of engagement with management and the implementation of one internal governance mechanism. This adjustment implies firms becoming even greener, as management has extra incentives for shifting towards green technology. Furthermore, it also leads to even greater shifts of real investment towards green firms, as social impact is also linked to the size of the company.

Formally, I start out with the same set up as Pástor, Stambaugh, and Taylor (2021). The model has one period from time 0 to time 1. There are N firms, $n = 1, ..., N$ with ESG characteristics g_n, which is an (Nx1) vector. $g_n > 0$ implies a green firm with positive ESG characteristics, respectively low emissions, and $g_n < 0$ implies a brown firm with negative ESG characteristics, respectively high emissions. $\tilde{r} = \mu + \tilde{v}$ defines firms' return in excess of the riskless rate r_f with $\tilde{\epsilon} \sim N(0, \Sigma)$. The social impact of a firms (S_n) is defined by the product of its ESG characteristics (g_n) and capital (K_n), formally $S_n \equiv g_n K_n$. A firm is endowed with capital $K_{0,n}$ and ESG characteristics $g_{0,n}$, but managers can change either subject to adjustment costs. A manager can choose how much capital (ΔK_n) to raise/ sell subject to capital adjustment costs $\frac{\kappa_n}{2}(\Delta K_n)^2$ and how much to change its ESG characteristic (Δg_n) subject to ESG adjustment costs $\frac{\chi_n}{2}(\Delta g_n)^2$.

Pástor, Stambaugh, and Taylor (2021) assume that manager's maximize firm value by choosing ΔK_n and Δg_n. Instead I assume that a manager is compensated with a proportion of firm value (ρv) and social impact $(\zeta \bar{d} S_n)$ and maximizes its compensation by choosing ΔK_n and Δg_n.

The investor side remains as in their model. There is a continuum of agents i with CARA utility $-e^{-A_i \tilde{W}_{1i} - b_i' X_i}$. A_i is the absolute risk aversion of agent i. $\tilde{W}_{1i} = W_{01}(1 + r_f + X_i' \tilde{r})$ is the wealth of agent i at time 1. X_i are portfolio weights of agent i (Nx1). $b_{i,n} = d_i g_n$ is a nonpecuniary benefit agent i derives from holding stock n. Without loss of generalization, one can assume that there are two types of investors. Investors with $d_i = 1$ care about ESG, while investors with $d_i = 0$ do not care about ESG.

The first step as in their model is to solve for optimal portfolio weights X by taking prices as given and to solve for prices by making markets clear. This lays the foundation. I skip reporting this step, as it is equivalent to their model. Instead I focus on the final step with my adjustment, i.e. the managers' optimal choice of ΔK_n and Δg_n. The firm's value at time 0 is given by the expected gross cash flow in time 1 less ESG adjustment costs and discounted by the cost of capital less time 0 capital adjustments. The cost of capital is given by 1+ the risk-free rate, the market risk and CAPM alpha which depends on the ESG characteristics:

$$v_n = -\Delta K_n - \frac{\kappa_n}{2}(\Delta K_n)^2 + \frac{\Pi(K_{0,n} + \Delta K_n)(1 - \frac{\chi_n}{2}(\Delta g_n)^2)}{1 + r_f + \mu_m \beta_n - \frac{\bar{d}}{a}(g_{0,n} + \Delta g_n)} \tag{A.3}$$

I assume that managers do not just maximize firm value v_n by choosing ΔK_n and Δg_n, but rather that their compensation Ξ_n by choosing ΔK_n and Δg_n, which is also linked to social impact $(S_n \equiv (K_{0,n} + \Delta K_n)(g_{0,n} + \Delta g_n))$:

$$\Xi_n = \rho v_n + \zeta \bar{d} S_n \tag{A.4}$$

The first order condition with respect to ΔK_n yields:

$$\begin{aligned}
&\max_{\Delta K_n} \rho[-\Delta K_n - \frac{\kappa_n}{2}(\Delta K_n)^2 + \frac{\Pi(K_{0,n}+\Delta K_n)(1-\frac{\chi_n}{2}(\Delta g_n)^2)}{1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}(g_{0,n}+\Delta g_n)}] + \zeta\bar{d}[(K_{0,n}+\Delta K_n)(g_{0,n}+\Delta g_n)] \\
&0 = -1 - \kappa_n\Delta K_n + \frac{\Pi_n(1-\frac{\chi_n}{2}(\Delta g_n)^2)}{1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}(g_{0,n}+\Delta g_n)} + \zeta\bar{d}(g_n+\Delta g_n) \\
&\Delta K_n(\bar{d}) = \frac{1}{\kappa_n}[\frac{\Pi_n(1-\frac{\chi_n}{2}(\Delta g_n)^2)}{1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}(g_{0,n}+\Delta g_n)}] + \frac{\zeta}{\rho}\bar{d}(g_n+\Delta g_n) - 1]
\end{aligned} \tag{A.5}$$

The first part is equivalent to Pástor, Stambaugh, and Taylor (2021) and highlights again that an increase in $\bar{d}$ reduces cost of capital for green firms increasing the net present value of projects and thus investments. The second part $\frac{\zeta}{\rho}\bar{d}(g_n+\Delta g_n)$ is new and highlights that the manager of a green firm is induced to raise even more capital with a higher $\bar{d}$, as this increases the payoff for social impact. Greater capital boosts total social impact and therefore increases manager's compensation and operates as additional payoff. This is moderated by how green $(g_n+\Delta g_n)$ the firm is and the relative fraction of compensation for social impact to firm value ($\frac{\zeta}{\rho}$).

Next I solve the first order condition with respect to Δg_n:

$$\max_{\Delta g_n} \rho[-\Delta K_n - \frac{\kappa_n}{2}(\Delta K_n)^2 + \frac{\Pi(K_{0,n}+\Delta K_n)(1-\frac{\chi_n}{2}(\Delta g_n)^2)}{1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}(g_{0,n}+\Delta g_n)}] + \zeta\bar{d}[(K_{0,n}+\Delta K_n)(g_{0,n}+\Delta g_n)] \tag{A.6}$$

I first drop terms without Δg_n and let $b = \rho\Pi(K_{0,n}+\Delta K_n)$ as well as $c = r_f + \mu_m\beta_n - \frac{\bar{d}}{a}g_{0,n}$ to simplify to

$$\begin{aligned}
&\max_{\Delta g_n} [\frac{b(1-\frac{\chi_n}{2}(\Delta g_n)^2)}{1+c-\frac{\bar{d}}{a}\Delta g_n}] + \zeta\bar{d}(K_{0,n}+\Delta K_n)\Delta g_n \\
&\max_{\Delta g_n} b[1-\frac{\chi_n}{2}(\Delta g_n)^2]\frac{1}{1+c-\frac{\bar{d}}{a}\Delta g_n} + \zeta\bar{d}(K_{0,n}+\Delta K_n)\Delta g_n \\
&\max_{\Delta g_n} b[1-\frac{\chi_n}{2}(\Delta g_n)^2]\frac{1}{1+c}\frac{1}{1-\frac{\bar{d}}{a(1+c)}\Delta g_n} + \zeta\bar{d}(K_{0,n}+\Delta K_n)\Delta g_n
\end{aligned} \tag{A.7}$$

Using the approximation $\frac{1}{1-y} \approx 1+y$, this further simplifies to:

$$\begin{aligned} &\max_{\Delta g_n} \; b[1-\frac{\chi_n}{2}(\Delta g_n)^2]\frac{1}{1+c}(1+\frac{\bar{d}}{a(1+c)}\Delta g_n)+\zeta\bar{d}(K_{0,n}+\Delta K_n)\Delta g_n \\ &\max_{\Delta g_n} \; \frac{b}{1+c}(1-\frac{\chi_n}{2}(\Delta g_n)^2+\frac{\bar{d}}{a(1+c)}\Delta g_n)+\zeta\bar{d}(K_{0,n}+\Delta K_n)\Delta g_n \end{aligned} \tag{A.8}$$

The first-order condition delivers:

$$\Delta g_n(\bar{d}) = \frac{\bar{d}}{a\chi_n} + \frac{(1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}g_{0,n})\zeta\bar{d}}{\rho\Pi\chi_n} \tag{A.9}$$

The first part ($\frac{\bar{d}}{a\chi_n}$) is again identical to Pástor, Stambaugh, and Taylor (2021) and highlights that managers maximizing market value of their firms make their firms greener when $\bar{d} > 0$, as the expected returns decrease in g_n and market value increases in g_n. With a low risk aversion a this effect is especially strong as ESG characteristics then have large effects on market values. The second term $\frac{(1+r_f+\mu_m\beta_n-\frac{\bar{d}}{a}g_{0,n})\zeta\bar{d}}{\rho\Pi\chi_n}$ is new. First, note from equation (9) in Pástor, Stambaugh, and Taylor (2021) that $-\frac{\bar{d}}{a}g_{0,n}$ is the CAPM alpha and the term in brackets is therefore generally positive. This implies that larger $\bar{d}$ creates extra incentives for making the firm greener scaled by the relative payoff for social impact and firm value. Specifically, it is increasing in the social impact payoff proportion (ζ), but decreasing in the firm value payoff proportion (ρ) and profitability (Π), which is equivalent to one plus the firm's gross profitability. This highlights the trade-off between social impact and firm value, i.e. accepting negative net present value projects that have large positive green characteristics. Interestingly, firms with more negative ESG endowments (small $g_{0,n}$) have a greater incentive to make their firms greener. $g_{0,n}$ and Δg_n have an equivalent weight on social capital, but adjustment costs in Δg_n are exponential. Thus, Δg_n has a bigger impact when starting at a small $g_{0,n}$. Higher adjustment costs (χ_n) reduces both components.

Appendix B

The CO2 Question: Technical Progress and the Climate Crisis

B.1 Appendix Tables

Table B.I. Patent Data by Country

The sample period is 2005-2020. In Panel A, we report the number of firm observations by country for the full (public and private), public, private and Trucost sample. Columns 1 to 4 report unconditional numbers and columns 5 to 8 condition on having at least one granted or purchased patent at the European Patent Office. In Panel B, we report patent counts and average patent counts by firm conditional on patenting. We report the total number of granted or purchased patents at the European Patent Office in a given country in columns 1 to 4 and the average number of patents at the European Patent Office per firm conditional on having at least one patent by country in columns 5 to 8. The full sample is based on firms from Orbis / Orbis IP, FactSet, Worldscope and Trucost. We report countries with less than 300 firm-year observations in the full sample aggregated by region under "Others". "Others North America" include ANGUILLA, ANTIGUA & BARBUDA, BAHAMAS, BARBADOS, BELIZE, COSTA RICA, CURACAO, DOMINICA, DOMINICAN REPUBLIC, EL SALVADOR, GRENADA, GREENLAND, GUATEMALA, HONDURAS, MARSHALL ISLANDS, NICARAGUA, SAINT BARTHELEMY, SAINT KITTS & NEVIS, SAINT LUCIA , SAINT MARTIN, SAINT PIERRE & MIQUELON, TRINIDAD & TOBAGO; "Others Asia" include ARMENIA, AZERBAIJAN, BAHRAIN, BHUTAN, CAMBODIA, KYRGYZSTAN, LAO PEOPLE'S DEMOCRATIC REPUBLIC, LEBANON, MACAO S.A.R, MYANMAR/BURMA, NEPAL, PALESTINIAN TERRITORIES, SYRIAN ARAB REPUBLIC; "Others Africa" include ALGERIA, BOTSWANA, CAMEROON, CAPE VERDE, COTE D'IVOIRE, ESWATINI, ETHIOPIA, GABON, GAMBIA, GHANA, KENYA, LIBERIA, MALAWI, MALI, MAYOTTE, MOZAMBIQUE, NAMIBIA, SENEGAL, SEYCHELLE, SUDAN, TOGO, TUNISIA, UGANDA, UNITED REPUBLIC OF TANZANIA, ZAMBIA; "Others Europe" include ALBANIA, BELARUS, FAROE ISLANDS, GEORGIA, GIBRALTAR, ISLE OF MAN, LIECHTENSTEIN, MONACO, SAN MARINO, SVALBARD and "Others South America" include FRENCH GUIANA, GUYANA, VENEZUELA.

Panel A: Firm count	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Patenting sample			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	179	87	92	18	9	8	1	3
AUSTRALIA	5579	1929	3650	628	520	388	132	155
AUSTRIA	1659	117	1542	49	241	69	172	33
BANGLADESH	184	134	50	7	0	0	0	0
BELGIUM	26834	202	26632	80	635	97	538	52
BERMUDA	805	710	95	67	62	53	9	7
BOLIVIA	33	0	33	0	0	0	0	0
BOSNIA & HERZEGOVINA	1734	39	1695	1	1	0	1	0
BRAZIL	1340	467	873	209	100	66	34	39
BULGARIA	15623	224	15399	5	31	8	23	2
CANADA	5976	5250	726	560	554	504	50	143
CANARY ISLANDS	1441	1	1440	0	1	0	1	0
CAYMAN ISLANDS	1412	723	689	44	55	34	21	6
CHILE	349	213	136	49	24	19	5	9
CHINA	86430	5116	81314	2751	1402	845	557	546
COLOMBIA	210	53	157	18	4	3	1	3
COTE D'IVOIRE	15	12	3	3	0	0	0	0
CROATIA	2452	144	2308	3	7	4	3	0
CYPRUS	1290	128	1162	10	19	3	16	1
CZECH REP	14076	24	14052	8	75	5	70	3
DENMARK	69409	218	69191	66	952	78	874	38
ECUADOR	62	1	61	0	0	0	0	0
EGYPT	710	210	500	41	7	5	2	2
ESTONIA	7286	19	7267	3	25	0	25	0
FINLAND	11009	185	10824	74	379	97	282	49
FRANCE	52481	861	51620	342	1714	401	1313	218
GERMANY	15731	1012	14719	315	1706	442	1264	199
GREECE	1595	278	1317	49	36	27	9	7
GUADELOUPE	109	1	108	0	0	0	0	0
GUERNSEY	103	79	24	14	9	7	2	2
HONG KONG	1360	1242	118	734	130	122	8	83
HUNGARY	4728	44	4684	6	28	6	22	2
ICELAND	2744	28	2716	6	20	4	16	1
INDIA	13529	4148	9381	721	394	286	108	148
INDONESIA	801	610	191	191	3	3	0	2
IRAQ	72	0	72	0	0	0	0	0
IRELAND	2160	126	2034	69	110	52	58	36
ISLAMIC REPUBLIC OF IRAN	470	0	470	0	0	0	0	0
ISLE OF MAN	51	36	15	5	4	2	2	1
ISRAEL	826	704	122	173	259	217	42	76
ITALY	68990	458	68532	181	1758	197	1561	99
JAMAICA	71	27	44	2	0	0	0	0
JAPAN	9292	5964	3328	2535	2507	2168	339	1077
JERSEY	124	87	37	17	17	12	5	6
JORDAN	214	174	40	6	3	3	0	1
KAZAKHSTAN	191	9	182	5	2	0	2	0
KENYA	32	26	6	11	0	0	0	0
KUWAIT	218	200	18	36	4	3	1	1
LATVIA	2550	26	2524	0	6	3	3	0
LIECHTENSTEIN	8	3	5	2	3	0	3	0
LITHUANIA	1246	41	1205	2	12	2	10	0
LUXEMBOURG	5397	97	5300	48	274	26	248	21
MALAYSIA	10471	1209	9262	255	76	55	21	26
MALTA	3719	26	3693	7	18	2	16	1
MARTINIQUE	110	1	109	0	0	0	0	0
MAURITIUS	421	86	335	5	3	2	1	0
MEXICO	257	168	89	89	31	23	8	15
MONGOLIA	259	47	212	2	0	0	0	0
MONTENEGRO	501	23	478	0	0	0	0	0
MOROCCO	143	42	101	18	5	2	3	1
NETHERLANDS	9800	224	9576	122	506	98	408	69
NEW ZEALAND	344	161	183	72	44	31	13	12
NIGERIA	150	109	41	23	0	0	0	0
NORTH MACEDONIA	1148	27	1121	0	3	0	3	0
NORWAY	43073	358	42715	123	617	108	509	51
OMAN	129	70	59	10	1	0	1	0
PAKISTAN	596	372	224	64	1	0	1	0
PALESTINIAN TERRITORIES	36	24	12	0	0	0	0	0
PANAMA	48	3	45	1	1	1	0	0
PARAGUAY	67	0	67	0	2	0	2	0
PERU	264	96	168	21	4	1	3	1
PHILIPPINES	502	296	206	83	13	6	7	6
POLAND	12888	887	12001	79	144	83	61	16
PORTUGAL	14538	65	14473	23	87	12	75	6
QATAR	57	49	8	34	4	2	2	0
REPUBLIC OF MOLDOVA	953	0	953	0	1	0	1	0
REUNION	210	1	209	0	2	0	2	0
ROMANIA	8326	105	8221	8	12	2	10	0
RUSSIA	44172	455	43717	85	119	40	79	19
SAUDI ARABIA	302	265	37	155	11	10	1	7
SERBIA	5521	29	5492	3	3	1	2	0
SINGAPORE	4156	845	3311	192	139	88	51	35
SLOVAKIA	5685	24	5661	0	23	3	20	0
SLOVENIA	3099	44	3055	4	43	7	36	1
SOUTH AFRICA	404	334	70	185	59	55	4	41
SOUTH KOREA	6097	2996	3101	1240	1222	884	338	507
SPAIN	44586	275	44311	115	605	85	520	54
SRI LANKA	268	249	19	5	1	1	0	1
SWEDEN	47755	911	46844	284	1253	378	875	159
SWITZERLAND	606	348	258	243	253	176	77	145
TAIWAN	3330	2508	822	904	684	616	68	288
THAILAND	2867	797	2070	233	33	26	7	14
TUNISIA	41	34	7	2	1	1	0	0
TURKEY	2202	480	1722	120	65	45	20	25
UKRAINE	27602	33	27569	6	2	0	2	0
UNITED ARAB EMIRATES	116	97	19	49	5	5	0	4
UNITED KINGDOM	33578	1939	31639	770	1490	571	919	308
UNITED STATES	15620	12610	3010	3863	4189	3670	519	1774
URUGUAY	120	0	120	0	0	0	0	0
UZBEKISTAN	271	0	271	0	0	0	0	0
VIETNAM	2880	758	2122	24	2	2	0	0
VIRIGIN ISL	194	140	54	2	9	8	1	0
ZIMBABWE	66	10	56	4	1	0	1	0
Others Africa	139	62	77	12	1	0	1	0
Others Asia	126	30	96	13	0	0	0	0
Others Australia	39	7	32	3	0	0	0	0
Others Europe	136	17	119	11	1	0	1	0
Others North America	235	55	180	8	5	5	0	1
Others South America	79	3	76	0	1	0	1	0
Total	801569	62372	739197	18820	25735	13213	12522	6497

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Patent count and firm average patent count								
	Patent count				Average no. of patents cond. on patenting			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	76	75	1	21	4.5	4.7	1.0	2.6
AUSTRALIA	3325	2585	740	1957	2.9	3.0	2.7	4.1
AUSTRIA	12601	7464	5137	5441	13.2	20.0	8.8	24.6
BANGLADESH	0	0	0	0	.	.	.	.
BELGIUM	14726	8352	6374	5961	7.5	18.8	4.2	22.4
BERMUDA	792	777	15	117	4.4	4.6	1.4	10.6
BOLIVIA	0	.	0	.	.	.	.	.
BOSNIA & HERZEGOVINA	3	0	3	0	1.5	.	1.5	.
BRAZIL	1285	1102	183	694	4.3	5.0	2.3	4.4
BULGARIA	49	8	41	2	1.1	1.1	1.1	1.0
CANADA	21968	20795	1173	12958	12.8	13.5	6.9	23.4
CANARY ISLANDS	1	0	1	.	1.0	.	1.0	.
CAYMAN ISLANDS	804	599	205	33	7.2	7.9	5.7	5.5
CHILE	1375	1364	11	768	14.6	15.9	1.4	14.8
CHINA	37617	28891	8726	25049	10.6	11.6	8.2	17.6
COLOMBIA	8	8	0	8	1.1	1.1	.	1.1
COTE D'IVOIRE	0	0	0	0	.	.	.	.
CROATIA	13	7	6	0	1.4	1.2	2.0	.
CYPRUS	45	7	38	5	1.7	1.8	1.7	2.5
CZECH REP	271	11	260	10	1.8	1.4	1.9	1.4
DENMARK	12411	5816	6595	5489	7.0	13.8	4.9	18.5
ECUADOR	0	.	0	.	.	.	.	.
EGYPT	446	436	10	2	21.2	29.1	1.7	2.0
ESTONIA	41	0	41	0	1.2	.	1.2	.
FINLAND	26134	23547	2587	22769	19.0	40.0	3.3	62.4
FRANCE	122478	90499	31979	86106	20.5	45.0	8.1	64.0
GERMANY	157802	120251	37551	109786	22.9	50.7	8.3	83.6
GREECE	115	95	20	35	1.5	1.6	1.1	1.6
GUADELOUPE	0	.	0	.	.	.	.	.
GUERNSEY	44	38	6	9	2.9	3.2	2.0	2.3
HONG KONG	6044	5972	72	5390	14.9	15.4	4.2	21.6
HUNGARY	314	199	115	134	4.6	6.0	3.3	7.4
ICELAND	776	449	327	31	9.7	15.0	6.5	15.5
INDIA	7222	6142	1080	5113	6.0	6.6	4.0	8.7
INDONESIA	4	4	0	3	1.0	1.0	.	1.0
IRAQ	0	.	0	.	.	.	.	.
IRELAND	5213	4249	964	3826	19.0	24.4	9.5	25.2
ISLAMIC REPUBLIC OF IRAN	0	.	0	.	.	.	.	.
ISLE OF MAN	3	1	2	1	1.0	1.0	1.0	1.0
ISRAEL	3388	3095	293	2003	4.6	4.9	2.5	8.1
ITALY	24565	12241	12324	10033	4.6	13.9	2.7	21.5
JAMAICA	0	0	0	0	.	.	.	.
JAPAN	335534	324725	10809	300059	27.3	29.2	9.1	48.0
JERSEY	68	59	9	44	2.6	3.1	1.3	3.1
JORDAN	11	11	0	0	1.2	1.2	.	.
KAZAKHSTAN	4	0	4	0	1.0	.	1.0	.
KENYA	0	0	0	0	.	.	.	.
KUWAIT	5	4	1	1	1.0	1.0	1.0	1.0
LATVIA	35	29	6	.	1.9	2.2	1.2	.
LIECHTENSTEIN	1114	0	1114	0	65.5	.	65.5	.
LITHUANIA	12	3	9	0	1.1	1.0	1.1	.
LUXEMBOURG	5418	944	4474	879	6.7	8.6	6.4	10.0
MALAYSIA	461	359	102	259	2.3	2.3	2.2	2.8
MALTA	65	1	64	1	1.9	1.0	1.9	1.0
MARTINIQUE	0	.	0	.	.	.	.	.
MAURITIUS	3	1	2	0	1.0	1.0	1.0	.
MEXICO	905	876	29	816	6.9	7.7	1.6	8.8
MONGOLIA	0	0	0	0	.	.	.	.
MONTENEGRO	0	0	0	.	.	.	.	.
MOROCCO	24	2	22	0	2.4	1.0	2.8	.
NETHERLANDS	45008	36806	8202	34510	31.6	67.8	9.3	79.9
NEW ZEALAND	364	264	100	177	3.2	3.3	3.0	6.1
NIGERIA	0	0	0	0	.	.	.	.
NORTH MACEDONIA	3	0	3	.	1.0	.	1.0	.
NORWAY	3658	2029	1629	1669	2.7	4.8	1.7	6.6
OMAN	1	0	1	0	1.0	.	1.0	.
PAKISTAN	2	0	2	0	1.0	.	1.0	.
PALESTINIAN TERRITORIES	0	0	0	.	.	.	.	.
PANAMA	0	0	0	0	.	.	.	.
PARAGUAY	2	.	2	.	1.0	.	1.0	.
PERU	5	1	4	1	1.3	1.0	1.3	1.0
PHILIPPINES	136	77	59	53	2.2	2.0	2.6	2.0
POLAND	933	748	185	207	3.1	3.8	1.7	4.9
PORTUGAL	362	39	323	22	1.8	1.5	1.8	1.4
QATAR	5	1	4	0	1.0	1.0	1.0	.
REPUBLIC OF MOLDOVA	1	.	1	.	1.0	.	1.0	.
REUNION	3	0	3	.	1.0	.	1.0	.
ROMANIA	11	2	9	0	1.1	2.0	1.0	.
RUSSIA	602	216	386	181	2.7	3.2	2.5	3.8
SAUDI ARABIA	4815	3226	1589	2488	145.9	119.5	264.8	191.4
SERBIA	4	2	2	0	1.3	2.0	1.0	.
SINGAPORE	1316	924	392	545	3.4	3.6	3.2	3.7
SLOVAKIA	52	12	40	.	1.3	1.7	1.2	.
SLOVENIA	246	153	93	62	2.6	5.7	1.4	6.9
SOUTH AFRICA	1376	1354	22	1322	8.0	8.4	2.2	9.1
SOUTH KOREA	111012	108110	2902	105775	30.4	38.0	3.6	55.0
SPAIN	6425	3573	2852	3118	4.0	9.0	2.4	11.5
SRI LANKA	1	1	0	1	1.0	1.0	.	1.0
SWEDEN	65379	54698	10681	51619	17.6	37.8	4.7	70.0
SWITZERLAND	44713	41808	2905	40503	33.0	39.3	10.0	46.8
TAIWAN	13945	13670	275	12050	7.1	7.5	1.8	11.4
THAILAND	721	705	16	633	6.4	7.0	1.3	7.9
TUNISIA	1	0	1	0	1.0	.	1.0	.
TURKEY	3354	3084	270	2868	15.7	18.0	6.3	23.3
UKRAINE	1	0	1	0	1.0	.	1.0	.
UNITED ARAB EMIRATES	26	25	1	25	2.4	2.5	1.0	2.5
UNITED KINGDOM	42199	29024	13175	27599	9.0	12.2	5.8	15.1
UNITED STATES	361345	353299	8046	301587	19.3	20.5	5.4	33.2
URUGUAY	0	.	0	.	.	.	.	.
UZBEKISTAN	0	.	0	.	.	.	.	.
VIETNAM	1	1	0	0	1.0	1.0	.	.
VIRIGIN ISL	32	31	1	0	1.6	1.6	1.0	.
ZIMBABWE	7	0	7	0	7.0	.	7.0	.
Others Africa	229	0	229	0	28.6	.	28.6	.
Others Asia	0	0	0	0	.	.	.	.
Others Australia	0	0	0	0	.	.	.	.
Others Europe	1	0	1	0	1.0	.	1.0	.
Others North America	139	139	0	7	6.9	6.9	.	2.3
Others South America	13	0	13	.	1.4	.	1.4	.
Total	1514067	1326115	187952	1192835	17.1	23.8	5.7	37.3

Table B.II. Patent Firm-Year Data by Country

The sample period is 2005-2020. We report the number of firm-year observations by country for the full (public and private), public, private and Trucost sample. The full sample is based on firms from Orbis/ Orbis IP, FactSet, Worldscope and Trucost. Countries with less than 300 firm-year observations in the full sample are aggregated by region under "Others" as in Table B.I. We report firm-year observations for the entire sample covering patenting and non-patenting firm-year observations in columns 1 to 4 as well as firm-year observations with at least one granted or purchased patent at the European Patent Office in columns 5 to 8.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Patenting sample			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	1261	541	720	130	17	16	1	8
AUSTRALIA	28788	8605	20183	4418	1144	865	279	472
AUSTRIA	10544	865	9679	421	958	373	585	221
BANGLADESH	909	415	494	40	0	0	0	0
BELGIUM	235974	1102	234872	595	1968	444	1524	266
BERMUDA	6339	5566	773	193	180	169	11	11
BOLIVIA	356	0	356	0	0	0	0	0
BOSNIA & HERZEGOVINA	13979	64	13915	1	2	0	2	0
BRAZIL	8103	3051	5052	1628	297	219	78	156
BULGARIA	112034	829	111205	31	45	7	38	2
CANADA	38973	33348	5625	3712	1717	1546	171	554
CANARY ISLANDS	11750	6	11744	0	1	0	1	0
CAYMAN ISLANDS	7456	3836	3620	88	112	76	36	6
CHILE	2493	1383	1110	509	94	86	8	52
CHINA	339786	38313	301473	12744	3547	2481	1066	1426
COLOMBIA	1559	369	1190	160	7	7	0	7
COTE D'IVOIRE	70	36	34	17	0	0	0	0
CROATIA	20425	424	20001	22	9	6	3	0
CYPRUS	4250	285	3965	27	26	4	22	2
CZECH REP	87217	117	87100	69	148	8	140	7
DENMARK	296922	1429	295493	541	1771	422	1349	297
ECUADOR	626	0	626	0	0	0	0	0
EGYPT	2475	995	1480	379	21	15	6	1
ESTONIA	57668	116	57552	21	33	0	33	0
FINLAND	85592	1660	83932	606	1374	588	786	365
FRANCE	396609	5270	391339	2628	5978	2013	3965	1346
GERMANY	99925	6314	93611	2248	6899	2373	4526	1313
GREECE	12962	1071	11891	356	78	60	18	22
GUADELOUPE	628	0	628	0	0	0	0	0
GUERNSEY	337	160	177	35	15	12	3	4
HONG KONG	10248	9272	976	3500	406	389	17	249
HUNGARY	40948	249	40699	69	68	33	35	18
ICELAND	22383	149	22234	13	80	30	50	2
INDIA	76694	15831	60863	4317	1210	937	273	590
INDONESIA	4111	3109	1002	1135	4	4	0	3
IRAQ	588	0	588	0	0	0	0	0
IRELAND	10561	571	9990	429	275	174	101	152
ISLAMIC REPUBLIC OF IRAN	3822	0	3822	0	0	0	0	0
ISLE OF MAN	186	72	114	15	3	1	2	1
ISRAEL	5260	4293	967	921	744	629	115	248
ITALY	575420	3026	572394	1307	5363	880	4483	467
JAMAICA	554	161	393	9	0	0	0	0
JAPAN	76771	48139	28632	16199	12311	11128	1183	6247
JERSEY	406	179	227	45	26	19	7	14
JORDAN	1051	630	421	41	9	9	0	0
KAZAKHSTAN	1557	59	1498	33	4	0	4	0
KENYA	208	141	67	88	0	0	0	0
KUWAIT	1103	877	226	129	5	4	1	1
LATVIA	19794	167	19627	0	18	13	5	0
LIECHTENSTEIN	50	20	30	14	17	0	17	0
LITHUANIA	6460	202	6258	15	11	3	8	0
LUXEMBOURG	21286	418	20868	245	809	110	699	88
MALAYSIA	80209	6320	73889	1654	200	153	47	93
MALTA	19845	73	19772	15	35	1	34	1
MARTINIQUE	610	0	610	0	0	0	0	0
MAURITIUS	1235	341	894	20	3	1	2	0
MEXICO	1690	1258	432	738	132	114	18	93
MONGOLIA	1278	4	1274	4	0	0	0	0
MONTENEGRO	3229	38	3191	0	0	0	0	0
MOROCCO	911	282	629	174	10	2	8	0
NETHERLANDS	45112	1392	43720	884	1425	543	882	432
NEW ZEALAND	2033	807	1226	425	113	80	33	29
NIGERIA	759	461	298	176	0	0	0	0
NORTH MACEDONIA	8772	73	8699	0	3	0	3	0
NORWAY	348158	2077	346081	746	1379	423	956	252
OMAN	813	321	492	79	1	0	1	0
PAKISTAN	3074	1533	1541	417	2	0	2	0
PALESTINIAN TERRITORIES	170	57	113	0	0	0	0	0
PANAMA	331	15	316	9	0	0	0	0
PARAGUAY	518	0	518	0	2	0	2	0
PERU	1835	653	1182	204	4	1	3	1
PHILIPPINES	4211	2731	1480	649	62	39	23	27
POLAND	70959	4116	66843	643	305	195	110	42
PORTUGAL	116018	381	115637	196	203	26	177	16
QATAR	390	340	50	205	5	1	4	0
REPUBLIC OF MOLDOVA	5211	0	5211	0	1	0	1	0
REUNION	1298	3	1295	0	3	0	3	0
ROMANIA	69425	455	68970	53	10	1	9	0
RUSSIA	297311	1845	295466	644	224	68	156	48
SAUDI ARABIA	1430	1213	217	390	33	27	6	13
SERBIA	41567	68	41499	16	3	1	2	0
SINGAPORE	17527	4834	12693	1160	382	259	123	149
SLOVAKIA	45549	82	45467	0	41	7	34	0
SLOVENIA	24892	158	24734	31	95	27	68	9
SOUTH AFRICA	2820	2396	424	1828	172	162	10	146
SOUTH KOREA	48207	19499	28708	7492	3651	2848	803	1924
SPAIN	360397	1615	358782	972	1608	398	1210	270
SRI LANKA	1315	1101	214	52	1	1	0	1
SWEDEN	337849	5748	332101	1741	3716	1447	2269	737
SWITZERLAND	4762	2576	2186	1899	1354	1064	290	866
TAIWAN	24896	18442	6454	5551	1975	1820	155	1061
THAILAND	21114	4541	16573	1409	113	101	12	80
TUNISIA	163	81	82	16	1	0	1	0
TURKEY	11677	2495	9182	827	214	171	43	123
UKRAINE	200831	93	200738	35	1	0	1	0
UNITED ARAB EMIRATES	681	532	149	260	11	10	1	10
UNITED KINGDOM	197087	10586	186501	7175	4673	2384	2289	1826
UNITED STATES	98517	81296	17221	24913	18697	17218	1479	9072
URUGUAY	497	0	497	0	0	0	0	0
UZBEKISTAN	1498	0	1498	0	0	0	0	0
VIETNAM	18615	2778	15837	143	1	1	0	0
VIRIGIN ISL	1153	839	314	6	20	19	1	0
ZIMBABWE	494	31	463	21	1	0	1	0
Others Africa	671	137	534	72	8	0	8	0
Others Asia	815	160	655	73	0	0	0	0
Others Australia	290	20	270	9	0	0	0	0
Others Europe	610	53	557	32	1	0	1	0
Others North America	1506	295	1211	21	20	20	0	3
Others South America	512	5	507	0	9	0	9	0
Total	5318818	390985	4927833	124222	88727	55786	32941	31942

Table B.III. Green/Brown Efficiency Innovation by Country

The sample period is 2005-2020. In Panel A, we report the number of firm observations with at least one green, resepctively brown efficiency, European Patent Office patent by country for the full (public and private), public, private and Trucost sample. In Panel B, we report green European Patent Office patent counts and average green European Patent Office patent counts by firm conditional on green patenting. In Panel C, we report brown efficiency European Patent Office patent counts and average brown efficiency European Patent Office patent counts by firm conditional on brown efficiency patenting. The full sample is based on firms from Orbis/ Orbis IP, FactSet, Worldscope and Trucost. Countries with less than 300 firm-year observations in the full sample are aggregated by region under "Others" as in Table B.I.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Firm count								
	with at least one green patent				with at least one brown efficiency patent			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	4	4	0	1	6	6	0	3
AUSTRALIA	134	106	28	44	51	41	10	20
AUSTRIA	81	36	45	23	55	24	31	16
BANGLADESH	0	0	0	0	0	0	0	0
BELGIUM	151	43	108	26	59	20	39	12
BERMUDA	16	15	1	3	10	10	0	4
BOLIVIA	0	0	0	0	0	0	0	0
BOSNIA & HERZEGOVINA	0	0	0	0	0	0	0	0
BRAZIL	35	21	14	16	11	9	2	6
BULGARIA	8	3	5	1	3	1	2	0
CANADA	164	153	11	53	49	47	2	27
CANARY ISLANDS	0	0	0	0	0	0	0	0
CAYMAN ISLANDS	10	8	2	2	3	2	1	0
CHILE	4	4	0	3	4	4	0	1
CHINA	438	294	144	228	135	99	36	80
COLOMBIA	1	1	0	1	1	1	0	1
COTE D'IVOIRE	0	0	0	0	0	0	0	0
CROATIA	0	0	0	0	1	0	1	0
CYPRUS	4	1	3	1	2	0	2	0
CZECH REP	11	0	11	0	4	0	4	0
DENMARK	227	32	195	23	68	12	56	11
ECUADOR	0	0	0	0	0	0	0	0
EGYPT	3	3	0	1	0	0	0	0
ESTONIA	5	0	5	0	1	0	1	0
FINLAND	124	44	80	32	58	24	34	21
FRANCE	427	174	253	120	172	81	91	66
GERMANY	575	219	356	132	293	115	178	80
GREECE	5	5	0	1	4	3	1	2
GUADELOUPE	0	0	0	0	0	0	0	0
GUERNSEY	2	2	0	1	1	1	0	1
HONG KONG	50	47	3	36	13	13	0	11
HUNGARY	6	2	4	1	4	2	2	0
ICELAND	3	1	2	0	0	0	0	0
INDIA	119	94	25	63	49	37	12	28
INDONESIA	0	0	0	0	0	0	0	0
IRAQ	0	0	0	0	0	0	0	0
IRELAND	32	25	7	18	16	12	4	7
ISLAMIC REPUBLIC OF IRAN	0	0	0	0	0	0	0	0
ISLE OF MAN	1	1	0	0	0	0	0	0
ISRAEL	61	48	13	23	19	17	2	11
ITALY	363	79	284	40	177	54	123	35
JAMAICA	0	0	0	0	0	0	0	0
JAPAN	1046	936	110	565	510	468	42	329
JERSEY	5	3	2	2	0	0	0	0
JORDAN	1	1	0	0	0	0	0	0
KAZAKHSTAN	2	0	2	0	0	0	0	0
KENYA	0	0	0	0	0	0	0	0
KUWAIT	0	0	0	0	0	0	0	0
LATVIA	2	1	1	0	0	0	0	0
LIECHTENSTEIN	1	0	1	0	1	0	1	0
LITHUANIA	1	0	1	0	1	0	1	0
LUXEMBOURG	78	6	72	5	52	8	44	6
MALAYSIA	18	15	3	9	14	8	6	8
MALTA	3	0	3	0	0	0	0	0
MARTINIQUE	0	0	0	0	0	0	0	0
MAURITIUS	0	0	0	0	0	0	0	0
MEXICO	11	9	2	9	8	7	1	6
MONGOLIA	0	0	0	0	0	0	0	0
MONTENEGRO	0	0	0	0	0	0	0	0
MOROCCO	3	1	2	1	0	0	0	0
NETHERLANDS	161	56	105	45	87	41	46	33
NEW ZEALAND	11	6	5	3	2	0	2	0
NIGERIA	0	0	0	0	0	0	0	0
NORTH MACEDONIA	0	0	0	0	0	0	0	0
NORWAY	168	45	123	28	67	23	44	15
OMAN	0	0	0	0	0	0	0	0
PAKISTAN	0	0	0	0	0	0	0	0
PALESTINIAN TERRITORIES	0	0	0	0	0	0	0	0
PANAMA	0	0	0	0	0	0	0	0
PARAGUAY	0	0	0	0	0	0	0	0
PERU	0	0	0	0	0	0	0	0
PHILIPPINES	3	2	1	2	1	0	1	0
POLAND	33	20	13	5	13	9	4	1
PORTUGAL	21	2	19	2	8	2	6	2
QATAR	0	0	0	0	1	0	1	0
REPUBLIC OF MOLDOVA	0	0	0	0	0	0	0	0
REUNION	0	0	0	0	0	0	0	0
ROMANIA	0	0	0	0	2	0	2	0
RUSSIA	23	10	13	5	10	4	6	3
SAUDI ARABIA	6	5	1	3	4	3	1	3
SERBIA	1	0	1	0	0	0	0	0
SINGAPORE	41	27	14	15	16	12	4	8
SLOVAKIA	3	0	3	0	1	0	1	0
SLOVENIA	11	4	7	1	3	1	2	0
SOUTH AFRICA	14	13	1	12	6	6	0	4
SOUTH KOREA	415	327	88	232	115	91	24	65
SPAIN	146	33	113	26	34	14	20	12
SRI LANKA	1	1	0	1	0	0	0	0
SWEDEN	306	125	181	67	124	61	63	39
SWITZERLAND	121	98	23	84	46	37	9	34
TAIWAN	199	186	13	110	29	29	0	19
THAILAND	9	9	0	8	3	3	0	3
TUNISIA	0	0	0	0	0	0	0	0
TURKEY	18	14	4	11	11	9	2	7
UKRAINE	0	0	0	0	0	0	0	0
UNITED ARAB EMIRATES	3	3	0	3	1	1	0	1
UNITED KINGDOM	406	220	186	148	197	107	90	77
UNITED STATES	1559	1414	145	863	539	511	28	366
URUGUAY	0	0	0	0	0	0	0	0
UZBEKISTAN	0	0	0	0	0	0	0	0
VIETNAM	0	0	0	0	0	0	0	0
VIRIGIN ISL	3	3	0	0	0	0	0	0
ZIMBABWE	1	0	1	0	0	0	0	0
Others Africa	1	0	1	0	1	0	1	0
Others Asia	0	0	0	0	0	0	0	0
Others Australia	0	0	0	0	0	0	0	0
Others Europe	0	0	0	0	1	0	1	0
Others North America	1	1	0	0	1	1	0	0
Others South America	1	0	1	0	1	0	1	0
Total	7854	4994	2860	3091	3145	2057	1088	1450

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Patent count and firm average patent count for *green* patents								
	Patent count				Average no. of patents cond. on patenting			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	11	11	0	1	3.7	3.7	.	1.0
AUSTRALIA	308	240	68	162	1.4	1.5	1.2	1.6
AUSTRIA	1070	773	297	519	4.3	5.7	2.7	5.4
BANGLADESH	0	0	0	0	.	.	.	.
BELGIUM	1991	1232	759	885	4.1	6.4	2.6	6.3
BERMUDA	68	67	1	29	2.4	2.5	1.0	9.7
BOLIVIA	0	.	0	.	.	.	.	.
BOSNIA & HERZEGOVINA	0	0	0	0	.	.	.	.
BRAZIL	163	117	46	107	2.0	2.1	2.0	2.2
BULGARIA	14	4	10	1	1.0	1.0	1.0	1.0
CANADA	2071	1998	73	1418	4.7	5.0	2.0	7.0
CANARY ISLANDS	0	0	0	.	.	.	.	.
CAYMAN ISLANDS	119	115	4	1	3.1	3.2	1.3	1.0
CHILE	186	186	0	104	6.0	6.0	.	5.5
CHINA	3260	2660	600	2347	3.9	4.3	2.7	5.2
COLOMBIA	4	4	0	4	1.3	1.3	.	1.3
COTE D'IVOIRE	0	0	0	0	.	.	.	.
CROATIA	0	0	0	0	.	.	.	.
CYPRUS	4	1	3	1	1.0	1.0	1.0	1.0
CZECH REP	16	0	16	0	1.1	.	1.1	.
DENMARK	3051	1689	1362	1663	6.7	11.3	4.5	12.8
ECUADOR	0	.	0	.	.	.	.	.
EGYPT	10	8	2	0	1.7	1.6	2.0	.
ESTONIA	12	0	12	0	1.5	.	1.5	.
FINLAND	1267	1021	246	968	3.3	4.3	1.7	4.7
FRANCE	12412	10239	2173	9892	8.1	12.1	3.2	13.8
GERMANY	19691	15808	3883	14728	10.7	16.6	4.4	20.0
GREECE	6	6	0	1	2.0	2.0	.	1.0
GUADELOUPE	0	.	0	.	.	.	.	.
GUERNSEY	8	8	0	2	2.7	2.7	.	2.0
HONG KONG	891	880	11	827	8.0	8.3	2.2	10.3
HUNGARY	6	3	3	2	1.2	1.5	1.0	2.0
ICELAND	3	1	2	0	1.0	1.0	1.0	.
INDIA	799	711	88	655	3.1	3.4	1.7	3.9
INDONESIA	0	0	0	0	.	.	.	.
IRAQ	0	.	0	.	.	.	.	.
IRELAND	348	311	37	271	5.2	6.0	2.5	5.9
ISLAMIC REPUBLIC OF IRAN	0	.	0	.	.	.	.	.
ISLE OF MAN	0	0	0	0	.	.	.	.
ISRAEL	247	226	21	133	1.8	1.9	1.2	2.0
ITALY	2116	1254	862	1092	2.4	4.3	1.5	5.4
JAMAICA	0	0	0	0	.	.	.	.
JAPAN	43713	41881	1832	39531	9.2	9.4	5.4	11.9
JERSEY	12	9	3	9	2.0	2.3	1.5	2.3
JORDAN	2	2	0	0	1.0	1.0	.	.
KAZAKHSTAN	2	0	2	0	1.0	.	1.0	.
KENYA	0	0	0	0	.	.	.	.
KUWAIT	0	0	0	0	.	.	.	.
LATVIA	4	3	1	.	1.0	1.0	1.0	.
LIECHTENSTEIN	37	0	37	0	2.6	.	2.6	.
LITHUANIA	0	0	0	0	.	.	.	.
LUXEMBOURG	311	100	211	81	1.8	3.2	1.5	3.4
MALAYSIA	35	30	5	23	1.1	1.1	1.0	1.1
MALTA	3	0	3	0	1.0	.	1.0	.
MARTINIQUE	0	.	0	.	.	.	.	.
MAURITIUS	0	0	0	0	.	.	.	.
MEXICO	76	74	2	71	2.1	2.1	1.0	2.2
MONGOLIA	0	0	0	0	.	.	.	.
MONTENEGRO	0	0	0	.	.	.	.	.
MOROCCO	10	1	9	0	1.4	1.0	1.5	.
NETHERLANDS	3916	3331	585	3198	8.3	13.1	2.7	14.8
NEW ZEALAND	27	6	21	3	2.1	1.2	2.6	1.0
NIGERIA	0	0	0	0	.	.	.	.
NORTH MACEDONIA	0	0	0	.	.	.	.	.
NORWAY	539	278	261	231	1.6	2.0	1.3	2.2
OMAN	0	0	0	0	.	.	.	.
PAKISTAN	0	0	0	0	.	.	.	.
PALESTINIAN TERRITORIES	0	0	0	.	.	.	.	.
PANAMA	0	0	0	0	.	.	.	.
PARAGUAY	0	.	0	.	.	.	.	.
PERU	0	0	0	0	.	.	.	.
PHILIPPINES	10	6	4	6	1.7	1.5	2.0	1.5
POLAND	70	59	11	18	1.6	1.7	1.1	1.6
PORTUGAL	33	4	29	4	1.2	1.0	1.2	1.0
QATAR	0	0	0	0	.	.	.	.
REPUBLIC OF MOLDOVA	0	.	0	.	.	.	.	.
REUNION	0	0	0	.	.	.	.	.
ROMANIA	0	0	0	0	.	.	.	.
RUSSIA	166	57	109	50	3.5	4.8	3.0	5.0
SAUDI ARABIA	671	561	110	474	33.5	40.1	18.3	52.7
SERBIA	1	0	1	0	1.0	.	1.0	.
SINGAPORE	219	153	66	109	1.9	2.0	1.8	2.0
SLOVAKIA	3	0	3	.	1.0	.	1.0	.
SLOVENIA	14	5	9	1	1.1	1.3	1.0	1.0
SOUTH AFRICA	149	148	1	144	3.1	3.1	1.0	3.3
SOUTH KOREA	20357	20067	290	19757	17.9	20.6	1.8	24.7
SPAIN	1967	1685	282	1624	6.3	16.0	1.4	17.5
SRI LANKA	1	1	0	1	1.0	1.0	.	1.0
SWEDEN	2720	1860	860	1680	3.4	4.6	2.2	5.6
SWITZERLAND	3826	3535	291	3443	8.2	9.1	3.6	10.0
TAIWAN	1303	1276	27	1124	2.9	3.0	1.2	3.6
THAILAND	99	98	1	97	2.4	2.5	1.0	2.5
TUNISIA	0	0	0	0	.	.	.	.
TURKEY	87	70	17	66	1.9	1.9	1.9	2.0
UKRAINE	0	0	0	0	.	.	.	.
UNITED ARAB EMIRATES	4	4	0	4	1.0	1.0	.	1.0
UNITED KINGDOM	4311	3174	1137	3005	3.8	4.4	2.8	4.9
UNITED STATES	27548	26791	757	21063	5.0	5.2	2.5	5.9
URUGUAY	0	.	0	.	.	.	.	.
UZBEKISTAN	0	.	0	.	.	.	.	.
VIETNAM	0	0	0	0	.	.	.	.
VIRIGIN ISL	5	5	0	0	1.3	1.3	.	.
ZIMBABWE	1	0	1	0	1.0	.	1.0	.
Others Africa	4	0	4	0	1.3	.	1.3	.
Others Asia	0	0	0	0	.	.	.	.
Others Australia	0	0	0	0	.	.	.	.
Others Europe	0	0	0	0	.	.	.	.
Others North America	1	1	0	0	1.0	1.0	.	.
Others South America	11	0	11	.	1.4	.	1.4	.
Total	162420	144848	17572	131630	6.7	8.0	2.9	9.8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Patent count and firm average patent count for *brown efficiency* patents								
	Patent count				Average no. of patents cond. on patenting			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	8	8	0	3	1.3	1.3	.	1.0
AUSTRALIA	159	138	21	88	1.6	1.6	1.5	1.7
AUSTRIA	507	121	386	104	3.8	1.6	6.3	1.7
BANGLADESH	0	0	0	0	.	.	.	.
BELGIUM	870	676	194	533	4.8	7.0	2.3	7.4
BERMUDA	28	28	0	5	1.4	1.4	.	1.3
BOLIVIA	0	.	0	.	.	.	.	.
BOSNIA & HERZEGOVINA	0	0	0	0	.	.	.	.
BRAZIL	30	28	2	25	1.4	1.4	1.0	1.5
BULGARIA	2	1	1	0	1.0	1.0	1.0	.
CANADA	407	403	4	264	2.9	2.9	1.0	3.0
CANARY ISLANDS	0	0	0	.	.	.	.	.
CAYMAN ISLANDS	54	53	1	0	4.5	4.8	1.0	.
CHILE	8	8	0	3	1.0	1.0	.	1.0
CHINA	563	330	233	247	2.4	1.9	3.8	1.9
COLOMBIA	1	1	0	1	1.0	1.0	.	1.0
COTE D'IVOIRE	0	0	0	0	.	.	.	.
CROATIA	1	0	1	0	1.0	.	1.0	.
CYPRUS	2	0	2	0	1.0	.	1.0	.
CZECH REP	4	0	4	0	1.0	.	1.0	.
DENMARK	331	43	288	40	2.8	1.4	3.3	1.5
ECUADOR	0	.	0	.	.	.	.	.
EGYPT	0	0	0	0	.	.	.	.
ESTONIA	1	0	1	0	1.0	.	1.0	.
FINLAND	726	632	94	613	4.0	6.0	1.3	6.4
FRANCE	5121	4672	449	4575	8.1	11.5	2.0	12.5
GERMANY	10572	9206	1366	8331	11.7	18.0	3.5	19.3
GREECE	5	4	1	3	1.0	1.0	1.0	1.0
GUADELOUPE	0	.	0	.	.	.	.	.
GUERNSEY	5	5	0	5	2.5	2.5	.	2.5
HONG KONG	115	115	0	113	3.8	3.8	.	4.0
HUNGARY	11	1	10	0	2.8	1.0	3.3	.
ICELAND	0	0	0	0	.	.	.	.
INDIA	302	261	41	219	2.2	2.5	1.2	2.3
INDONESIA	0	0	0	0	.	.	.	.
IRAQ	0	.	0	.	.	.	.	.
IRELAND	133	128	5	122	5.1	5.8	1.3	6.8
ISLAMIC REPUBLIC OF IRAN	0	.	0	.	.	.	.	.
ISLE OF MAN	0	0	0	0	.	.	.	.
ISRAEL	84	82	2	19	2.4	2.5	1.0	1.2
ITALY	1383	914	469	682	2.8	4.2	1.7	4.9
JAMAICA	0	0	0	0	.	.	.	.
JAPAN	15564	15066	498	14258	7.3	7.5	4.2	8.8
JERSEY	0	0	0	0	.	.	.	.
JORDAN	0	0	0	0	.	.	.	.
KAZAKHSTAN	0	0	0	0	.	.	.	.
KENYA	0	0	0	0	.	.	.	.
KUWAIT	0	0	0	0	.	.	.	.
LATVIA	0	0	0	.	.	.	.	.
LIECHTENSTEIN	4	0	4	0	1.0	.	1.0	.
LITHUANIA	0	0	0	0	.	.	.	.
LUXEMBOURG	179	26	153	25	1.9	1.4	2.0	1.4
MALAYSIA	29	22	7	20	1.1	1.2	1.0	1.2
MALTA	0	0	0	0	.	.	.	.
MARTINIQUE	0	.	0	.	.	.	.	.
MAURITIUS	0	0	0	0	.	.	.	.
MEXICO	23	22	1	20	1.3	1.3	1.0	1.3
MONGOLIA	0	0	0	0	.	.	.	.
MONTENEGRO	0	0	0	.	.	.	.	.
MOROCCO	0	0	0	0	.	.	.	.
NETHERLANDS	572	450	122	442	2.9	3.8	1.6	3.9
NEW ZEALAND	2	0	2	0	1.0	.	1.0	.
NIGERIA	0	0	0	0	.	.	.	.
NORTH MACEDONIA	0	0	0	.	.	.	.	.
NORWAY	204	133	71	115	1.5	1.9	1.1	1.9
OMAN	0	0	0	0	.	.	.	.
PAKISTAN	0	0	0	0	.	.	.	.
PALESTINIAN TERRITORIES	0	0	0	.	.	.	.	.
PANAMA	0	0	0	0	.	.	.	.
PARAGUAY	0	.	0	.	.	.	.	.
PERU	0	0	0	0	.	.	.	.
PHILIPPINES	2	0	2	0	2.0	.	2.0	.
POLAND	82	78	4	22	3.4	3.9	1.0	3.1
PORTUGAL	7	2	5	2	1.0	1.0	1.0	1.0
QATAR	1	0	1	0	1.0	.	1.0	.
REPUBLIC OF MOLDOVA	0	.	0	.	.	.	.	.
REUNION	0	0	0	.	.	.	.	.
ROMANIA	2	1	1	0	1.0	1.0	1.0	.
RUSSIA	14	8	6	7	1.3	1.6	1.0	1.8
SAUDI ARABIA	290	255	35	213	16.1	21.3	5.8	26.6
SERBIA	0	0	0	0	.	.	.	.
SINGAPORE	70	50	20	46	1.6	1.7	1.5	1.8
SLOVAKIA	1	0	1	.	1.0	.	1.0	.
SLOVENIA	3	0	3	0	1.0	.	1.0	.
SOUTH AFRICA	18	18	0	15	1.2	1.2	.	1.3
SOUTH KOREA	2041	1942	99	1873	5.3	5.7	2.3	6.1
SPAIN	80	39	41	38	1.4	1.7	1.2	1.7
SRI LANKA	0	0	0	0	.	.	.	.
SWEDEN	1927	1537	390	1465	5.2	6.7	2.7	7.4
SWITZERLAND	541	485	56	467	3.3	3.6	2.1	3.7
TAIWAN	82	81	1	74	1.5	1.6	1.0	1.6
THAILAND	29	29	0	29	1.8	1.8	.	1.8
TUNISIA	0	0	0	0	.	.	.	.
TURKEY	58	54	4	50	1.6	1.6	1.0	1.7
UKRAINE	0	0	0	0	.	.	.	.
UNITED ARAB EMIRATES	0	0	0	0	.	.	.	.
UNITED KINGDOM	4619	2773	1846	2739	8.7	8.5	9.0	9.0
UNITED STATES	15966	15659	307	12878	8.4	8.5	4.3	9.0
URUGUAY	0	.	0	.	.	.	.	.
UZBEKISTAN	0	.	0	.	.	.	.	.
VIETNAM	0	0	0	0	.	.	.	.
VIRIGIN ISL	0	0	0	0	.	.	.	.
ZIMBABWE	0	0	0	0	.	.	.	.
Others Africa	15	0	15	0	3.0	.	3.0	.
Others Asia	0	0	0	0	.	.	.	.
Others Australia	0	0	0	0	.	.	.	.
Others Europe	1	0	1	0	1.0	.	1.0	.
Others North America	1	1	0	0	1.0	1.0	.	.
Others South America	1	0	1	.	1.0	.	1.0	.
Total	63861	56589	7272	50793	6.6	7.6	3.2	8.4

Table B.IV. Distributions of Patent Ratios

The sample period is 2005-2020. We report average patent ratios for the full (public and private), public, private and Trucost sample by country in Panel A, by GICS 6-Industry in Panel B, and by year in Panel C. Countries with less than 300 firm-year observations in the full sample are aggregated by region under "Others" as in Table B.I. We report the average *GREENRATIOEP* in columns 1 to 4 and the average *BROWNEFFRATIOEP* in columns 5 to 8. *GREENRATIOEP* is the number of green patents over the total number of patents granted or purchased at the firm and year level based on European Patent Office patents. *BROWNEFFRATIOEP* similarly is the number of brown efficiency patents over the total number of patents at the European Patent Office.

Panel A: Patent ratio by country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENRATIOEP (in %)				BROWNEFFRATIOEP (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	3.431	3.646	0	2.083	17.157	18.229	0	21.875
AUSTRALIA	11.820	11.106	14.033	9.587	5.536	6.303	3.159	6.384
AUSTRIA	10.090	11.574	9.143	9.645	4.036	3.823	4.172	4.031
BELGIUM	10.016	12.547	9.278	14.196	2.777	5.042	2.117	5.433
BERMUDA	7.001	6.865	9.091	16.651	7.527	8.017	0	13.912
BOSNIA & HERZEGOVINA	0		0		0		0	
BRAZIL	14.423	11.860	21.616	15.956	1.982	2.156	1.496	2.298
BULGARIA	27.778	50.000	23.684	50.000	3.333	7.143	2.632	0
CANADA	14.952	14.943	15.027	16.274	3.370	3.601	1.288	3.476
CANARY ISLANDS	0		0		0		0	
CAYMAN ISLANDS	17.005	24.333	1.535	2.381	2.279	2.042	2.778	0
CHILE	8.534	9.328	0	11.928	2.777	3.035	0	0.129
CHINA	12.895	12.712	13.320	13.883	2.630	2.742	2.368	2.651
COLOMBIA	42.857	42.857		42.857	14.286	14.286		14.286
CROATIA	0	0	0		2.778	0	8.333	
CYPRUS	6.090	6.250	6.061	12.500	7.692	0	9.091	0
CZECH REP	9.009	0	9.524	0	2.365	0	2.500	0
DENMARK	14.661	13.861	14.911	15.292	3.351	1.971	3.782	2.296
EGYPT	11.003	8.737	16.667	0	0	0	0	0
ESTONIA	24.242		24.242		3.030		3.030	
FINLAND	11.156	12.131	10.426	14.699	5.174	4.937	5.352	6.480
FRANCE	9.410	11.005	8.600	11.561	2.399	2.887	2.151	2.957
GERMANY	9.829	12.580	8.387	14.677	3.670	4.130	3.428	5.142
GREECE	3.846	5.000	0	4.545	5.449	5.417	5.556	10.227
GUERNSEY	6.222	7.778	0	8.333	11.111	13.889	0	41.667
HONG KONG	11.811	11.607	16.492	12.372	0.895	0.934	0	1.158
HUNGARY	4.070	3.788	4.337	5.556	5.719	3.030	8.254	0
ICELAND	1.750	0.667	2.400	0	0	0	0	0
INDIA	9.668	9.765	9.337	11.933	5.432	4.475	8.715	5.691
INDONESIA	0	0		0	0	0		0
IRELAND	7.409	8.122	6.182	7.572	2.190	1.507	3.366	1.020
ISLE OF MAN	0	0	0	0	0	0	0	0
ISRAEL	8.493	7.964	11.390	7.689	1.806	1.818	1.739	1.800
ITALY	8.405	11.101	7.876	11.569	4.470	7.808	3.815	7.857
JAPAN	11.974	11.933	12.363	13.117	4.009	4.190	2.311	4.486
JERSEY	14.853	12.431	21.429	16.871	0	0	0	0
JORDAN	22.222	22.222			0	0		
KAZAKHSTAN	50.000		50.000		0		0	
KUWAIT	0	0	0	0	0	0	0	0
LATVIA	10.648	7.051	20.000		0	0	0	
LIECHTENSTEIN	2.941		2.941		0.307		0.307	
LITHUANIA	0	0	0		0	0	0	
LUXEMBOURG	8.876	7.933	9.024	4.758	5.086	3.172	5.387	2.828
MALAYSIA	10.953	11.377	9.574	12.131	7.248	7.060	7.859	9.465
MALTA	8.571	0	8.824	0	0	0	0	0
MAURITIUS	0	0	0		0	0	0	
MEXICO	11.866	11.986	11.111	14.065	4.499	4.333	5.556	3.967
MOROCCO	44.833	50.000	43.542		0	0	0	
NETHERLANDS	12.803	12.364	13.073	12.195	3.662	3.030	4.050	3.352
NEW ZEALAND	6.245	3.369	13.215	5.271	0.983	0	3.367	0
NORTH MACEDONIA	0		0		0		0	
NORWAY	16.378	13.005	17.870	12.324	5.511	5.150	5.671	5.507
OMAN	0		0		0		0	
PAKISTAN	0		0		0		0	
PARAGUAY	0		0		0		0	
PERU	0	0	0	0	0	0	0	0
PHILIPPINES	9.677	10.256	8.696	14.815	0.645	0	1.739	0
POLAND	8.738	9.714	7.009	8.097	3.534	4.075	2.576	2.749
PORTUGAL	10.755	13.462	10.358	21.875	3.448	7.692	2.825	12.500
QATAR	0	0	0		20.000	0	25.000	
REPUBLIC OF MOLDOVA	0		0		0		0	
REUNION	0		0		0		0	
ROMANIA	0	0	0		15.000	50.000	11.111	
RUSSIA	18.115	15.124	19.419	17.780	1.629	1.779	1.563	1.479
SAUDI ARABIA	14.928	16.602	7.391	19.058	4.057	4.475	2.178	4.298
SERBIA	33.333	0	50.000		0	0	0	
SINGAPORE	16.440	17.319	14.588	19.931	5.226	5.325	5.018	7.019
SLOVAKIA	7.317	0	8.824		2.439	0	2.941	
SLOVENIA	8.574	2.596	10.948	1.852	1.729	0	2.416	0
SOUTH AFRICA	13.326	13.531	10.000	12.959	4.299	4.564	0	3.009
SOUTH KOREA	15.313	16.177	12.250	17.506	2.753	2.880	2.304	3.130
SPAIN	13.898	18.612	12.347	23.800	1.844	1.841	1.845	2.707
SRI LANKA	100.000	100.000		100.000	0	0		0
SWEDEN	10.044	8.926	10.757	7.739	3.387	3.696	3.189	5.302
SWITZERLAND	10.205	9.203	13.881	9.153	1.721	1.844	1.269	1.988
TAIWAN	11.846	11.718	13.346	11.997	0.913	0.936	0.645	1.040
THAILAND	11.684	12.577	4.167	15.567	1.710	1.913	0	2.415
TUNISIA	0		0		0		0	
TURKEY	4.534	4.443	4.895	3.690	2.461	2.493	2.333	3.034
UKRAINE	0		0		0		0	
UNITED ARAB EMIRATES	23.485	25.833	0	25.833	0	0	0	0
UNITED KINGDOM	10.455	11.534	9.330	10.907	4.215	3.933	4.508	4.397
UNITED STATES	10.084	9.975	11.351	10.046	2.594	2.705	1.301	3.205
VIETNAM	0	0			0	0		
VIRIGIN ISL	18.333	19.298	0		0	0	0	
ZIMBABWE	14.286		14.286		0		0	
Others Africa	1.030		1.030		6.425		6.425	
Others Europe	0		0		100.000		100.000	
Others North America	0.333	0.333		0	0.556	0.556		0
Others South America	83.333		83.333		11.111		11.111	
Total	11.025	11.420	10.356	12.108	3.313	3.357	3.238	3.737

Panel B: Patent ratio by GICS-6 industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENRATIOEP (in %)				BROWNEFFRATIOEP (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Aerospace & Defense	9.492	9.719	8.443	9.142	5.539	5.787	4.394	6.052
Air Freight & Logistics	8.466	7.540	14.286	6.616	0.140	0.162	0	0.176
Airlines	3.856	4.351	0	3.520	1.318	1.487	0	1.705
Auto Components	9.436	9.159	10.920	10.058	8.571	8.897	6.821	7.116
Automobiles	26.585	25.135	50.806	24.230	14.375	14.882	5.914	15.878
Banks	8.923	7.953	8.963	7.554	3.198	3.142	3.200	2.862
Beverages	11.315	11.483	10.590	12.240	0.445	0.548	0	0.642
Biotechnology	16.187	15.842	17.120	17.474	0.527	0.066	1.770	0.028
Building Products	11.655	12.982	8.336	12.635	6.164	6.110	6.299	4.587
Capital Markets	9.757	9.184	10.002	8.949	3.576	3.096	3.782	2.446
Chemicals	14.032	14.708	11.415	14.545	3.386	3.427	3.227	3.631
Commercial Services & Supplies	9.342	9.728	9.122	9.935	4.887	4.927	4.864	4.980
Communications Equipment	5.010	5.061	4.735	4.859	0.473	0.515	0.245	0.238
Construction Materials	23.040	21.477	29.663	23.978	9.282	9.857	6.845	8.658
Construction & Engineering	20.136	22.291	17.918	25.216	9.106	10.894	7.266	11.395
Consumer Finance	9.115	6.233	9.909	7.222	6.164	8.333	5.566	9.722
Containers & Packaging	3.985	3.590	5.014	3.757	0.509	0.528	0.459	0.471
Distributors	4.788	3.876	6.127	4.832	3.454	1.314	6.596	1.479
Diversified Consumer Services	6.048	0.111	7.571	0.390	2.204	0.297	2.693	1.039
Diversified Financial Services	8.471	8.471		8.671	5.316	5.316		4.935
Diversified Telecommunication Services	3.296	3.354	3.118	2.053	0.200	0.240	0.079	0.099
Electric Utilities	51.136	47.124	63.475	44.165	11.261	12.972	6.000	14.053
Electrical Equipment	28.966	31.305	21.217	32.485	3.620	3.546	3.868	3.780
Electronic Equipment, Instruments & Components	11.617	11.447	13.201	11.268	1.586	1.519	2.212	1.362
Energy Equipment & Services	14.896	13.723	40.333	13.969	19.947	20.498	8.000	20.610
Entertainment	6.579	4.961	22.222	1.755	0	0	0	0
Equity Real Estate Investment Trusts (REITs)	9.201	10.112	9.065	25.532	2.644	0.727	2.932	0
Food Products	12.321	11.457	15.193	11.788	0.580	0.682	0.240	0.959
Food & Staples Retailing	8.831	7.140	10.408	7.078	1.946	0.806	3.008	0
Gas Utilities	36.688	37.006	33.333	40.735	7.004	6.615	11.111	7.446
Health Care Equipment & Supplies	4.054	3.687	5.569	3.969	0.408	0.420	0.362	0.349
Health Care Providers & Services	7.601	8.711	6.123	7.269	0.227	0.398	0	0.108
Health Care Technology	8.689	8.689		8.253	0.040	0.040		0.048
Hotels, Restaurants & Leisure	2.809	1.641	5.286	2.506	2.481	0.794	6.061	0
Household Durables	5.729	5.613	6.643	7.087	2.405	2.512	1.565	3.161
Household Products	5.400	5.400		5.114	1.253	1.253		0.649
IT Services	7.414	4.591	18.511	4.550	2.093	1.558	4.198	1.450
Independent Power and Renewable Electricity Producers	53.779	48.510	65.170	49.417	12.500	14.531	8.108	21.250
Industrial Conglomerates	12.975	12.975		13.045	5.100	5.100		5.065
Insurance	8.517	8.334	8.681	7.572	1.775	3.399	0.318	2.989
Interactive Media & Services	3.000	3.000		3.111	0.143	0.143		0.148
Internet Software & Services (discont. 2018)	2.430	0.544	55.556	0.681	0.007	0.007	0	0.009
Internet & Direct Marketing Retail	4.197	2.861	7.345	3.692	1.183	0.966	1.695	0.327
Leisure Products	8.814	9.868	1.762	12.864	1.277	1.468	0	1.909
Life Sciences Tools & Services	11.390	11.390		11.224	0.431	0.431		0.530
Machinery	8.267	8.156	8.569	8.839	6.890	7.532	5.147	8.299
Marine	15.618	11.964	20.204	12.761	7.920	6.185	10.098	6.597
Media	5.163	4.091	8.333	4.039	0.819	1.096	0	0.031
Media (discont. 2018)	5.066	5.249	3.906	5.908	1.126	1.304	0	0.566
Metals & Mining	12.383	12.883	10.869	12.266	6.881	6.713	7.390	6.877
Multi-Utilities	36.686	36.686		37.253	11.821	11.821		12.005
Multiline Retail	8.252	9.407	0	10.225	0	0	0	0
Oil, Gas & Consumable Fuels	32.787	33.905	27.825	38.453	11.463	11.503	11.284	9.716
Paper & Forest Products	10.728	10.720	10.781	11.814	1.104	1.252	0.062	1.171
Personal Products	4.031	4.381	2.179	2.891	0.172	0.205	0	0.117
Pharmaceuticals	7.661	7.456	8.395	5.992	0.072	0.074	0.063	0.074
Professional Services	10.444	14.152	9.778	8.848	2.790	4.488	2.485	6.967
Real Estate Management & Development	12.212	20.018	10.191	17.834	3.442	2.031	3.807	1.760
Road & Rail	18.871	16.711	22.547	14.477	0.667	0	1.802	0
Semiconductors & Semiconductor Equipment	17.679	17.930	16.305	20.064	0.895	0.669	2.127	0.653
Software	4.186	3.293	6.757	1.935	1.185	0.737	2.473	0.228
Specialty Retail	8.227	6.460	11.112	5.651	1.015	1.329	0.501	0.495
Technology Hardware, Storage & Peripherals	4.723	4.872	3.272	4.816	0.489	0.481	0.574	0.528
Textiles, Apparel & Luxury Goods	5.157	4.702	6.723	3.595	0.700	0.422	1.659	0.245
Thrifts & Mortgage Finance	0	0			0	0		
Tobacco	11.293	11.094	12.941	10.258	2.034	2.279	0	2.417
Trading Companies & Distributors	10.525	10.847	10.360	10.904	3.847	5.536	2.976	3.283
Transportation Infrastructure	7.022	3.427	10.205	2.326	2.273	0	4.286	0
Water Utilities	20.029	19.940	20.238	29.206	5.579	5.291	6.250	1.111
Wireless Telecommunication Services	2.232	2.232		2.016	0.158	0.158		0.166
Total	11.025	11.420	10.356	12.108	3.313	3.357	3.238	3.737

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Patent ratio by year								
	GREENRATIOEP (in %)				BROWNEFFRATIOEP (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
2005	7.975	8.363	7.201	9.147	2.835	3.044	2.419	3.408
2006	8.039	8.761	6.590	9.120	3.171	3.386	2.741	4.487
2007	8.975	9.679	7.558	9.734	3.174	3.494	2.531	3.703
2008	8.682	9.736	6.639	10.598	3.282	3.395	3.062	4.080
2009	9.496	10.210	8.131	10.784	3.029	3.294	2.522	3.819
2010	10.036	10.531	9.065	11.105	3.113	3.175	2.991	4.024
2011	10.151	10.747	9.076	11.356	3.337	3.474	3.090	4.261
2012	10.966	11.366	10.353	12.992	3.413	3.758	2.884	4.811
2013	11.839	11.911	11.728	12.626	3.311	3.607	2.854	4.192
2014	11.983	12.264	11.502	13.725	3.460	3.256	3.810	3.688
2015	11.582	12.157	10.625	13.242	3.507	3.451	3.599	4.219
2016	12.117	12.794	11.076	13.012	3.251	3.244	3.263	3.505
2017	12.152	12.094	12.241	11.983	3.615	3.397	3.951	3.353
2018	12.097	12.132	12.046	12.054	3.560	3.484	3.669	3.802
2019	12.783	13.482	11.791	13.404	3.276	3.193	3.393	3.318
2020	12.959	13.064	12.754	13.173	3.203	2.980	3.639	2.970
Total	11.025	11.420	10.356	12.108	3.313	3.357	3.238	3.737

Table B.V. Summary Statistics of Quantitative Variables

The table reports sample averages, medians, and standard deviations of various firm-level characteristics for the period 2005 to 2020. Panel A reports summary statistics for the entire sample (public and private) firms, while summary statistics in Panel B are based on the Trucost sample. Column 1 to 3 aggregate all firm-years with at least one patent at the European Patent Office. Column 4 to 6 aggregate firm-years without any patent at the European Patent Office. Column 7 to 9 aggregate firm-years in the bottom decile based on a firm's average *GREENRATIOEP* across the whole period. This covers only firms with 0 green patents and represents about about 35% of firm-year observations in Panel B. Column 10 to 12 aggregate firm-years in the top decile based on a firm's average *GREENRATIOEP* across the whole period. *OECDRATIOEP* is a patent ratio based on OECD green Env-tech classification, calculated as the number of granted or purchased OECD patents over the total number of granted or purchased patents; *GREENRATIOEP2* is defined as the number of granted or purchased "green" or "general efficiency" patents over the total number of granted or purchased patents; other patent variables are defined in Table 3.2 and Table 3.4; emission variables are defined in Table 3.2 and Table 3.6; LOGCAPEX is the natural logarithm of capital expenditures; LOGCASH is the natural logarithm of cash and short-term equivalents; other financial variables are defined in Table 3.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All public and private firms												
	Patenting Sample			Sample w/o patents			Bottom decile green ratio			Top decile green ratio		
	mean	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*
GREENRATIOEP (in %)	10.996	0	26.077	.	.	.	0	0	0	75.156	100.000	36.455
BROWNEFFRATIOEP (in %)	3.328	0	14.494	.	.	.	2.719	0	15.267	2.675	0	13.159
GREENRATIOEP2 (in %)	19.594	0	32.851	.	.	.	9.506	0	27.027	78.557	100.000	34.126
OECDRATIOEP (in %)	11.476	0	26.442	.	.	.	5.453	0	20.884	47.628	50.000	45.337
LOGASSETS	4.949	4.878	2.762	1.705	1.144	1.755	4.382	4.335	2.519	4.785	4.661	2.832
LOGPPE	3.517	3.129	3.034	0.824	0.090	1.558	2.957	2.435	2.783	3.505	2.960	3.145
LEVERAGE	15.839	9.308	18.557	10.359	0	18.612	14.768	7.127	18.626	16.585	9.275	19.504
ROE	4.735	7.540	35.930	10.123	5.990	35.817	4.464	7.240	36.837	2.373	6.430	38.912
INVEST/A	5.449	3.296	7.039	4.307	0.431	8.451	5.502	3.144	7.322	5.866	3.478	7.496
LOGCAPEX	2.354	1.900	2.174	0.466	0.010	1.054	1.887	1.423	1.868	2.334	1.751	2.295
LOGCASH	3.123	2.931	2.427	0.546	0.076	1.075	2.580	2.315	2.149	2.948	2.680	2.405
Panel B: Public firms with emission data												
	Patenting Sample			Sample w/o patents			Bottom decile green ratio			Top decile green ratio		
	mean	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*
GREENRATIOEP (in %)	12.107	0	24.172	.	.	.	0	0	0	67.280	75.000	35.579
BROWNEFFRATIOEP (in %)	3.737	0	13.298	.	.	.	2.431	0	14.157	4.400	0	14.787
GREENRATIOEP2 (in %)	21.955	8.642	30.406	.	.	.	13.008	0	29.908	72.057	86.667	33.297
OECDRATIOEP (in %)	12.377	0	24.179	.	.	.	4.727	0	18.624	46.206	44.444	41.557
GREENCITMAXEP	61.153	1.000	610.518	.	.	.	0	0	0	57.471	12.000	147.651
BROWNEFFCITMAXEP	15.378	0	155.893	.	.	.	0.748	0	11.176	8.101	0	42.833
GREENCOUNTBBEP	0.238	0	1.256	.	.	.	0	0	0	0.453	0	1.355
BROWNEFFCOUNTBBEP	0.093	0	0.920	.	.	.	0.004	0	0.069	0.042	0	0.270
LOGS1TOT	6.129	5.921	2.765	4.854	4.536	2.780	5.275	5.046	2.561	6.691	6.259	3.462
LOGS2TOT	6.054	6.098	2.241	4.752	4.770	2.029	5.317	5.356	2.101	5.887	5.971	2.501
LOGS3UPTOT	7.964	8.136	2.260	6.315	6.346	1.967	7.141	7.303	2.121	7.841	8.073	2.557
LOGS3DOWNTOT	7.084	7.492	3.440	6.022	6.213	2.907	6.232	6.589	3.137	7.497	7.895	3.826
LOGS3TOT	8.417	8.540	2.652	7.206	7.170	2.188	7.636	7.815	2.419	8.583	8.810	3.027
S1INT	1.606	0.189	4.710	2.264	0.160	6.267	1.362	0.161	4.462	3.285	0.375	6.993
S2INT	0.407	0.211	0.561	0.414	0.195	0.577	0.353	0.176	0.521	0.503	0.245	0.661
S3UPINT	2.086	1.609	1.716	1.486	0.764	1.697	1.791	1.091	1.741	2.281	1.804	1.645
S3DOWNINT	7.273	1.539	14.603	5.793	1.048	13.555	5.837	0.980	13.203	12.128	2.985	19.340
S3INT	9.407	3.704	15.167	7.458	2.412	14.182	7.787	2.791	13.834	14.450	5.478	19.756
LOGSIZE	7.857	7.894	1.761	6.931	6.983	1.553	7.371	7.388	1.713	7.589	7.659	1.881
LOGPPE	6.200	6.275	2.219	5.028	5.208	2.306	5.493	5.562	2.178	6.426	6.363	2.535
LEVERAGE	23.140	21.705	17.162	24.614	22.122	19.727	22.607	20.136	18.443	24.738	23.591	17.608
ROE	8.191	10.122	27.004	8.605	9.484	23.861	6.818	9.705	29.198	3.923	8.717	31.006
M/B	2.799	1.843	3.026	2.421	1.508	2.812	2.940	1.897	3.268	2.558	1.626	2.890
BETA	0.636	0.693	0.381	0.687	0.695	0.277	0.617	0.659	0.331	0.709	0.732	0.385
VOLAT	0.103	0.087	0.070	0.109	0.090	0.081	0.107	0.089	0.075	0.118	0.096	0.088
MOM	0.006	0.007	0.036	0.003	0.004	0.038	0.005	0.006	0.036	0.005	0.005	0.042
RET	0.018	0.013	0.118	0.014	0.005	0.123	0.019	0.011	0.124	0.017	0.007	0.136
INVEST/A	4.705	3.621	4.370	4.533	2.573	5.796	4.604	3.312	4.712	5.651	4.351	5.255
MSCI	0.405	0	0.491	0.189	0	0.391	0.293	0	0.455	0.369	0	0.483
LOGCAPEX	4.596	4.620	2.018	3.431	3.437	1.914	3.968	3.948	1.934	4.665	4.624	2.293
LOGCASH	5.726	5.719	1.776	4.698	4.724	1.719	5.182	5.171	1.670	5.566	5.613	1.826
AGE	49.171	36.000	39.423	35.312	25.000	30.027	41.570	30.000	34.030	41.168	27.000	36.030

Table B.VI. Green Patent Ratio and Firm Type - Industry by Industry

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOEP*. The key independent variables of interest are *LOGS1TOT*, *AGE*, and *PATSTOCKGREENEP*. We additionally include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All intedependent variabels are lagged by one year and defined in Table 3.1 and Table 3.2. We run the regression individually for each 6-digit GICS Industry with a Poisson pseudo-maximum likelihood regression and include country and year fixed effects. We double cluster standard errors at the firm and year dimension. We report the coefficient and standard error for *LOGS1TOT* in column 1, for *AGE* in column 2 and for *PATSTOCKGREENEP* in column 3 with *** representing 1% significance, ** 5% significance * 10% significance. Column 4 reports the Pseudo R2, column 5 the number of observations in the regression and column 6 the industry average absolute scope 1 emissions by which we rank the table.

Industry	(1) coef (std. err) LOGS1TOT	(2) coef (std. err) AGE (/100)	(3) coef (std. err) PATSTOCKGREENEP (/100)	(4) Pseudo R2	(5) N	(6) Industry Scope 1
Electric Utilities	0.013 (0.062)	-1.142*** (0.350)	0.269** (0.118)	0.091	254	21966773
Oil, Gas & Consumable Fuels	0.011 (0.061)	-0.065 (0.094)	0.002 (0.031)	0.052	559	20973912
Independent Power and Renewable Electricity Producers	-1.628*** (0.000)	296.113*** (0.000)	-147.142*** (0.000)	0.221	35	18641614
Metals & Mining	-0.187*** (0.068)	-0.090 (0.207)	0.271* (0.155)	0.090	827	16138911
Construction Materials	0.305 (0.212)	0.433 (0.385)	-1.198 (0.979)	0.149	236	9916635
Multi-Utilities	0.064 (0.080)	-0.615 (0.475)	0.640 (0.411)	0.122	116	7344608
Chemicals	-0.020 (0.031)	-0.140 (0.085)	0.041*** (0.011)	0.037	2128	4744375
Industrial Conglomerates	0.049 (0.035)	0.299 (0.202)	0.021*** (0.007)	0.152	448	1538727
Food Products	0.271*** (0.062)	0.102 (0.191)	1.273*** (0.278)	0.101	719	1141156
Construction & Engineering	0.128* (0.068)	0.376 (0.249)	1.158*** (0.290)	0.093	512	845274
Paper & Forest Products	0.519* (0.299)	0.621 (0.532)	0.867 (1.369)	0.177	223	805302
Diversified Financial Services	-0.018 (0.045)	0.631 (0.476)	0.166 (0.185)	0.151	239	729626
Commercial Services & Supplies	-0.277** (0.129)	-0.558 (0.384)	0.189 (0.831)	0.138	370	696769
Road & Rail	3.472*** (0.000)	na	200.565*** (0.000)	0.208	9	647088
Gas Utilities	0.005 (0.271)	-5.682** (2.758)	-5.525 (3.534)	0.160	55	617602
Trading Companies & Distributors	-0.055 (0.093)	-0.626* (0.348)	0.322 (0.444)	0.172	185	591652
Air Freight & Logistics	0.037 (0.319)	-2.605 (6.275)	-4.720 (3.967)	0.241	39	448489
Hotels, Restaurants & Leisure	7.278*** (0.000)	na	na	0.083	6	426348
Building Products	-0.234*** (0.080)	-0.355* (0.202)	0.483*** (0.091)	0.093	480	380646
Machinery	0.043 (0.058)	-0.097 (0.094)	0.161*** (0.034)	0.046	2420	350582
Energy Equipment & Services	0.124** (0.056)	0.305 (0.229)	-0.106 (0.185)	0.093	414	342478
Containers & Packaging	-0.260 (0.241)	-2.216** (1.007)	1.036 (1.383)	0.253	313	319053
Automobiles	0.021 (0.092)	-0.640*** (0.179)	0.017** (0.008)	0.104	418	264498
Electronic Equipment, Instruments & Components	-0.073 (0.053)	-0.054 (0.191)	0.086*** (0.012)	0.053	1440	255883
Specialty Retail	2.477*** (0.000)	na	9.560*** (0.000)	0.187	6	248423
Beverages	0.152 (0.339)	2.565*** (0.689)	0.738 (0.655)	0.278	170	224142
Semiconductors & Semiconductor Equipment	-0.108*** (0.031)	-0.582** (0.278)	0.274*** (0.067)	0.084	1299	204997
Insurance	0.328 (0.485)	-0.208 (0.631)	2.226 (2.489)	0.321	98	199957
Auto Components	-0.107 (0.093)	-0.344* (0.200)	0.390*** (0.059)	0.067	1013	198076
Real Estate Management & Development	2.663*** (0.000)	na	-34.207*** (0.000)	0.059	14	174526
Pharmaceuticals	-0.079 (0.075)	-0.393** (0.167)	0.185*** (0.048)	0.068	1443	168450
Household Durables	0.095 (0.100)	0.371 (0.332)	0.037*** (0.014)	0.084	626	126895
Entertainment	-1.262** (0.618)	-17.906*** (5.493)	5.241** (2.264)	0.357	41	126049
Textiles, Apparel & Luxury Goods	-0.233 (0.214)	-2.312*** (0.849)	3.064*** (0.969)	0.230	369	125082
Household Products	-0.047 (0.109)	0.941** (0.453)	0.372 (0.381)	0.211	177	111966
Health Care Providers & Services	-0.132 (0.170)	-1.047* (0.612)	8.769** (3.979)	0.248	210	109853
Electrical Equipment	-0.112*** (0.037)	-0.723*** (0.143)	0.151*** (0.023)	0.141	833	109565
Technology Hardware, Storage & Peripherals	-0.011 (0.085)	0.026 (0.325)	0.190*** (0.072)	0.091	674	101589
Aerospace & Defense	0.246*** (0.081)	-0.341* (0.188)	0.177* (0.091)	0.093	569	89730
Wireless Telecommunication Services	-0.555** (0.268)	-1.379 (1.116)	-1.199 (5.829)	0.329	124	88311
Tobacco	-0.782** (0.303)	2.102* (1.123)	0.958 (0.974)	0.238	108	74380
Diversified Telecommunication Services	-1.977*** (0.341)	5.329*** (0.969)	-5.309* (2.872)	0.364	277	55247
Equity Real Estate Investment Trusts (REITs)	0.447*** (0.000)	na	-9.172*** (0.000)	0.091	6	47687
Personal Products	0.300 (0.253)	-1.199 (0.843)	0.579 (1.057)	0.244	190	45429
Banks	0.113 (0.219)	-0.639 (0.474)	-0.214 (0.353)	0.119	279	36212
Internet & Direct Marketing Retail	-10.864** (4.746)	-185.218** (86.651)	45.821*** (17.154)	0.403	48	30579
Health Care Equipment & Supplies	0.273** (0.134)	-0.538 (0.381)	1.264*** (0.441)	0.142	1019	29296
Media (discont. 2018)	0.872*** (0.195)	1.078** (0.477)	-1.298 (2.884)	0.265	206	27369
Media	0.627 (0.605)	-5.134 (3.465)	59.782** (23.360)	0.530	40	26301
IT Services	0.140 (0.181)	-1.578*** (0.592)	0.443* (0.233)	0.213	335	20489
Capital Markets	0.058 (0.121)	-0.502 (0.327)	0.676*** (0.153)	0.187	330	17109
Life Sciences Tools & Services	0.172 (0.110)	-0.599 (0.495)	0.791*** (0.197)	0.101	289	16775
Communications Equipment	-0.346* (0.183)	1.771*** (0.604)	0.469 (0.380)	0.218	400	15302
Leisure Products	0.342** (0.140)	0.688** (0.280)	0.659*** (0.105)	0.310	237	15171
Biotechnology	-0.295*** (0.049)	-1.269* (0.726)	2.206*** (0.197)	0.122	1012	13626
Software	-0.897*** (0.335)	4.866** (2.098)	-0.226 (0.554)	0.244	566	9776
Interactive Media & Services	-0.719*** (0.190)	-85.065* (45.813)	2.841 (1.905)	0.218	33	4414
Health Care Technology	0.611*** (0.000)	na	5.137*** (0.000)	0.263	7	1291

Table B.VII. Brown Efficiency Patent Ratio and Firm Type - Industry by Industry

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *BROWNEFFRATIOEP*. The key independent variables of interest are *LOGS1TOT*, *AGE*, and *PATSTOCKBROWNEFFEP*. We additionally include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All intedependent variabels are lagged by one year and defined in Table 3.1 and Table 3.2. We run the regression individually for each 6-digit GICS Industry with a Poisson pseudo-maximum likelihood regression and include country and year fixed effects. We double cluster standard errors at the firm and year dimension. We report the coefficient and standard error for *LOGS1TOT* in column 1, for *AGE* in column 2 and for *PATSTOCKBROWNEFFEP* in column 3 with *** representing 1% significance, ** 5% significance * 10% significance. Column 4 reports the Pseudo R2, column 5 the number of observations in the regression and column 6 the industry average absolute scope 1 emissions by which we rank the table.

Industry	(1) coef (std. err) LOGS1TOT	(2) coef (std. err) AGE (/100)	(3) coef (std. err) PATSTOCKBROWNEFFEP (/100)	(4) Pseudo R2	(5) N	(6) Industry Scope 1
Electric Utilities	0.498*** (0.174)	0.916 (0.753)	8.859* (4.843)	0.239	232	21966773
Oil, Gas & Consumable Fuels	0.123 (0.128)	0.103 (0.160)	0.102 (0.113)	0.095	545	20973912
Independent Power and Renewable Electricity Producers	0.210*** (0.000)	na	-0.949*** (0.000)	0.054	8	18641614
Metals & Mining	-0.179** (0.072)	-0.587* (0.309)	0.770*** (0.236)	0.098	822	16138911
Construction Materials	-0.051 (0.229)	-0.090 (0.697)	5.102* (2.987)	0.170	218	9916635
Multi-Utilities	-0.154 (0.286)	-0.096 (0.868)	2.247 (2.478)	0.277	108	7344608
Chemicals	0.024 (0.103)	-0.107 (0.125)	0.357*** (0.092)	0.102	2034	4744375
Industrial Conglomerates	-0.238*** (0.063)	0.585* (0.341)	0.003 (0.028)	0.182	385	1538727
Food Products	0.511 (0.334)	-2.062* (1.061)	25.834*** (7.804)	0.363	471	1141156
Construction & Engineering	-0.031 (0.100)	-0.191 (0.402)	2.691*** (0.833)	0.115	523	845274
Diversified Financial Services	0.076 (0.064)	0.054 (0.698)	0.775 (0.589)	0.257	221	729626
Commercial Services & Supplies	0.029 (0.237)	-3.009** (1.239)	19.910** (8.770)	0.346	273	696769
Gas Utilities	-8.108*** (0.000)	na	-27.317*** (0.000)	0.081	10	617602
Trading Companies & Distributors	-0.647*** (0.191)	-3.213*** (0.697)	-0.807 (0.738)	0.264	94	591652
Building Products	-0.351** (0.152)	0.161 (0.317)	2.054*** (0.488)	0.145	479	380646
Machinery	-0.120** (0.052)	0.326*** (0.111)	0.167*** (0.029)	0.078	2392	350582
Energy Equipment & Services	-0.126** (0.058)	-0.032 (0.217)	0.223*** (0.048)	0.109	437	342478
Containers & Packaging	0.519 (0.547)	-1.205 (1.344)	25.427 (20.988)	0.430	173	319053
Automobiles	-0.073 (0.131)	1.498*** (0.300)	0.000 (0.010)	0.087	415	264498
Electronic Equipment, Instruments & Components	-0.022 (0.110)	2.036*** (0.355)	0.390*** (0.066)	0.155	1278	255883
Semiconductors & Semiconductor Equipment	0.318 (0.237)	1.843 (1.442)	5.967 (4.528)	0.275	1235	204997
Insurance	1.658*** (0.000)	-6.201*** (0.000)	-3.978*** (0.000)	0.286	83	199957
Auto Components	-0.155* (0.084)	0.033 (0.221)	0.273*** (0.047)	0.062	995	198076
Pharmaceuticals	0.382 (0.310)	-1.299 (0.863)	2.399 (1.584)	0.239	811	168450
Household Durables	0.057 (0.166)	-0.452 (0.439)	1.802*** (0.399)	0.293	572	126895
Household Products	-1.445*** (0.344)	-4.200*** (1.162)	2.298 (10.168)	0.620	129	111966
Health Care Providers & Services	-0.246*** (0.000)	na	na	0.010	10	109853
Electrical Equipment	-0.111 (0.113)	0.308 (0.392)	1.137*** (0.227)	0.144	799	109565
Technology Hardware, Storage & Peripherals	-0.216 (0.136)	4.414** (1.985)	2.786 (7.346)	0.500	627	101589
Aerospace & Defense	0.020 (0.129)	0.314 (0.266)	0.105*** (0.029)	0.126	547	89730
Tobacco	-0.863 (0.874)	5.265 (4.827)	4.440 (5.273)	0.307	87	74380
Banks	-2.585** (1.319)	-1.674* (0.875)	-2.420 (1.600)	0.347	186	36212
Health Care Equipment & Supplies	0.478 (0.291)	0.252 (0.991)	12.868*** (4.730)	0.171	774	29296
Media (discont. 2018)	37.065*** (0.000)	-53.910*** (0.000)	-781.612*** (0.000)	0.587	123	27369
IT Services	0.914*** (0.335)	-0.711 (0.932)	27.555*** (10.118)	0.630	298	20489
Capital Markets	0.277 (0.185)	0.287 (0.726)	-1.139 (2.909)	0.406	212	17109
Life Sciences Tools & Services	0.329 (0.341)	2.224 (2.293)	-18.939 (29.499)	0.300	198	16775
Communications Equipment	0.371 (0.416)	4.158*** (1.611)	-17.779** (8.267)	0.262	264	15302
Leisure Products	0.633 (0.527)	0.656 (0.777)	36.615*** (10.973)	0.442	167	15171
Professional Services	-4.365*** (0.000)	na	-75.640*** (0.000)	0.172	6	9864
Software	-5.699*** (1.821)	26.915 (18.620)	104.187*** (33.025)	0.627	198	9776
Interactive Media & Services	0.459*** (0.000)	na	-35.920*** (0.000)	0.103	6	4414

Table B.VIII. Patent Ratios and Firm Type: Alternative "green" Classifications

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is OECDRATIOEP in columns 1 to 3 and GREENRATIOEP2 in columns 4 to 6. All variables are defined in Table 3.1 and Table B.V. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	OECDRATIOEP			*GREENRATIOEP2*		
LOGS1TOT	0.095***	−0.017	−0.008	0.038***	−0.029***	−0.001
	(0.007)	(0.010)	(0.015)	(0.005)	(0.007)	(0.010)
AGE (/100)	−0.103***	−0.068**		−0.228***	−0.116***	
	(0.029)	(0.028)		(0.023)	(0.022)	
PATSTOCKGREENEP (/100)	0.044***	0.019***	−0.001	0.030***	0.023***	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
LOGSIZE	−0.174***	−0.039**	0.023	−0.033***	−0.033***	0.035**
	(0.016)	(0.017)	(0.023)	(0.012)	(0.012)	(0.016)
LOGPPE	0.124***	0.051***	−0.051**	0.043***	0.047***	−0.036**
	(0.016)	(0.016)	(0.025)	(0.011)	(0.011)	(0.016)
LEVERAGE	−0.002***	−0.000	0.003**	−0.002***	−0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROE	−0.031	−0.063	0.054	−0.087**	−0.070**	0.015
	(0.058)	(0.051)	(0.037)	(0.036)	(0.034)	(0.024)
M/B	0.002	0.006	−0.005	0.000	0.015***	−0.001
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
INVEST/A	0.002	0.005*	0.007**	0.008***	0.008***	0.005**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
BETA	0.363***	0.070*	0.018	0.246***	0.062**	−0.027
	(0.035)	(0.036)	(0.026)	(0.025)	(0.026)	(0.019)
VOLAT	1.273***	1.241***	−0.016	1.074***	0.875***	0.008
	(0.235)	(0.272)	(0.241)	(0.180)	(0.181)	(0.143)
MOM	0.850*	−0.598	0.384	0.274	−0.162	−0.058
	(0.473)	(0.460)	(0.299)	(0.329)	(0.333)	(0.220)
RET	−0.227*	−0.182	−0.067	−0.143	−0.109	0.011
	(0.126)	(0.119)	(0.078)	(0.088)	(0.086)	(0.056)
MSCI	0.009	0.029	−0.034	0.045**	0.054**	0.033
	(0.031)	(0.030)	(0.036)	(0.023)	(0.022)	(0.026)
Constant	2.181***	2.932***	3.486***	−1.942***	−1.242***	−1.104***
	(0.093)	(0.098)	(0.206)	(0.069)	(0.070)	(0.137)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	no	yes	no	no	yes	no
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	27854	24843	20299	27873	25985	23546
Pseudo R2	0.0930	0.342	0.511	0.0169	0.0986	0.162

Table B.IX. Worldwide Patent Ratios and Firm Type

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOWW* in columns 1 to 3 and *BROWNEFFRATIOWW* in columns 4 to 6. *GREENRATIOWW* is the number of green patent families over the total number of patent families granted or purchased at the firm and year level from any patent office worldwide. *BROWNEFFRATIOWW* similarly is the number of brown efficiency patent families over the total number of patent families at any patent office worldwide. All other variables are defined in Table 3.1 and Table 3.2. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOWW			*BROWNEFFRATIOWW*		
LOGS1TOT	0.105***	−0.022**	−0.008	0.094***	0.042***	0.000
	(0.006)	(0.009)	(0.011)	(0.010)	(0.016)	(0.027)
AGE (/100)	−0.289***	−0.118***		0.067	0.049	
	(0.029)	(0.027)		(0.041)	(0.042)	
PATSTOCKGREENWW (/100)	0.013***	0.008***	0.001			
	(0.001)	(0.001)	(0.001)			
PATSTOCKBROWNEFFWW (/100)				0.031***	0.015***	−0.004**
				(0.002)	(0.002)	(0.002)
LOGSIZE	−0.152***	−0.068***	0.001	−0.297***	−0.096***	−0.060
	(0.013)	(0.015)	(0.018)	(0.026)	(0.027)	(0.041)
LOGPPE	0.083***	0.091***	0.008	0.241***	0.056**	0.075
	(0.013)	(0.014)	(0.019)	(0.025)	(0.025)	(0.047)
LEVERAGE	−0.005***	−0.003***	0.001	−0.006***	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROE	−0.289***	−0.088**	0.050*	0.307***	0.147*	0.036
	(0.046)	(0.041)	(0.027)	(0.074)	(0.076)	(0.065)
M/B	0.013***	0.012**	−0.003	−0.021**	−0.003	−0.010
	(0.005)	(0.005)	(0.004)	(0.009)	(0.009)	(0.011)
INVEST/A	0.015***	0.007***	−0.000	0.013***	0.007	0.006
	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)	(0.005)
BETA	0.190***	0.051	−0.040*	0.270***	−0.013	−0.061
	(0.031)	(0.032)	(0.023)	(0.054)	(0.050)	(0.046)
VOLAT	1.541***	1.353***	0.010	−0.236	−0.594	−0.377
	(0.224)	(0.175)	(0.142)	(0.402)	(0.423)	(0.392)
MOM	−0.007	−0.737**	0.259	0.601	−0.113	−0.244
	(0.383)	(0.358)	(0.234)	(0.671)	(0.657)	(0.553)
RET	0.025	−0.013	−0.016	−0.046	0.205	0.321**
	(0.098)	(0.092)	(0.058)	(0.180)	(0.177)	(0.145)
MSCI	0.029	0.018	0.056*	−0.049	0.062	−0.017
	(0.028)	(0.027)	(0.030)	(0.051)	(0.048)	(0.059)
Constant	1.962***	2.530***	3.058***	1.074***	2.055***	2.660***
	(0.079)	(0.078)	(0.149)	(0.146)	(0.156)	(0.380)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	52568	49362	37346	52339	43021	23558
Pseudo R2	0.0948	0.315	0.565	0.140	0.425	0.556

Table B.X. Path Ratios and Firm Type: Alternative Industry Specifications

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variable is GREENRATIOEP in columns 1 to 4 and BROWNEFFRATIOEP in columns 5 to 8. We include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and MSCI. All variables are defined in Table 3.1 and Table 3.2. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. All regressions include country and year fixed effects. Column 1 and 5 additionally include industry fixed effects based on the 6-digit level GICS Industry, while column 3 and 7 add industry as well as the industry-year interaction. Column 2 and 6 additionally include year fixed effects and industry fixed effects based on the 8-digit level GICS Subindustry, while column 4 and 8 also include the industry-year interaction. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENRATIOEP				*BROWNEFFRATIOEP*			
LOGS1TOT	−0.032***	−0.036***	−0.033***	−0.036***	−0.010	0.013	−0.009	0.012
	(0.009)	(0.010)	(0.009)	(0.010)	(0.018)	(0.018)	(0.017)	(0.017)
AGE (/100)	−0.160***	−0.154***	−0.163***	−0.144***	0.193***	0.202***	0.191***	0.199***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.049)	(0.049)	(0.048)	(0.048)
PATSTOCKGREENEP (/100)	0.046***	0.047***	0.046***	0.047***				
	(0.004)	(0.004)	(0.004)	(0.004)				
PATSTOCKBROWNEFFEP (/100)					0.058***	0.056***	0.067***	0.066***
					(0.009)	(0.009)	(0.009)	(0.009)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	GICS Ind	GICS Sub Ind	GICS Ind	GICS Sub Ind	GICS Ind	GICS Sub Ind	GICS Ind	GICS Sub Ind
Industry-Year F.E.	no	no	GICS Ind	GICS Sub Ind	no	no	GICS Ind	GICS Sub Ind
Observations	27860	27687	27419	26513	27309	26411	23637	22225
Pseudo R2	0.196	0.216	0.224	0.256	0.277	0.301	0.286	0.329

Table B.XI. Patent Ratios and Firm Type: Legacy Sample

The unit of observation is firm-year. The sample period is 2005-2020 and the sample restricts inclusion of firms into those that Trucost covers in its database before 2016. The dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. Panel A covers all firm-years, while we further restricts inclusion in Panel B to firm-years with *at least one* green patent at the European Patent Office in columns 1 to 3 and one brown efficiency patent at the European Patent Office in columns 4 to 6. We include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and MSCI. All variables are defined in Table 3.1 and Table 3.2. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GREENRATIOEP			*BROWNEFFRATIOEP*		
Panel A: All firm years						
LOGS1TOT	0.101***	−0.040***	0.014	0.063***	0.056***	−0.065**
	(0.008)	(0.012)	(0.016)	(0.014)	(0.020)	(0.033)
AGE (/100)	−0.311***	−0.185***		0.269***	0.273***	
	(0.034)	(0.032)		(0.046)	(0.052)	
PATSTOCKGREENEP (/100)	0.052***	0.039***	−0.002			
	(0.004)	(0.004)	(0.003)			
PATSTOCKBROWNEFFEP (/100)				0.102***	0.044***	−0.000
				(0.010)	(0.008)	(0.008)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	no	yes	no	no	yes	no
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	22990	20155	18374	22922	16164	11588
Pseudo R2	0.0948	0.361	0.509	0.0973	0.450	0.522
Panel B: Firm-years with at least one green/ brown efficiency patent						
LOGS1TOT	1.626***	−1.631***	−0.356	0.370*	−0.122	−0.263
	(0.174)	(0.256)	(0.275)	(0.198)	(0.345)	(0.508)
AGE (/100)	−6.883***	−3.265***		−0.743	−0.141	
	(0.614)	(0.608)		(0.656)	(0.815)	
PATSTOCKGREENEP (/100)	0.720***	0.996***	0.478***			
	(0.090)	(0.109)	(0.072)			
PATSTOCKBROWNEFFEP (/100)				1.316***	0.951***	0.272*
				(0.149)	(0.168)	(0.142)
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	no	yes	no	no	yes	no
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes
Observations	11022	9776	10602	5211	4222	4905
R2	0.193	0.551	0.804	0.176	0.533	0.753
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes

Table B.XII. Patent Ratios and Firm Type: Excluding M&A firms

The unit of observation is firm-year. The sample period is 2005-2020 and restricits inclusion to firms without green or brown efficiency M&A activity between 2005 and 2020. Specifically, we drop firms that acquired a target with one or more green patents granted by the EPO between 2005 and 2020 in columns 1 to 3 and one or more brown efficiency patents granted by the EPO between 2005 and 2020 in columns 3 to 6. In Panel A, the dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. In Panel B, the dependent variable is GREENCITMAXEP in columns 1 to 3 and BROWNEFFCITMAXEP in columns 4 to 6. In Panel C, the dependent variable is GREENCOUNTBBEP in columns 1 to 3 and BROWNEFFCOUNTBBEP in columns 4 to 6. We include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and MSCI. All variables are defined in Table 3.1, Table 3.2 and Table 3.4. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and Trucost industry-year fixed effects and columns 3 and 6 year and firm fixed effects. We double cluster standard errors at the firm and year dimension.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Patent ratio						
	GREENRATIOEP			BROWNEFFRATIOEP		
LOGS1TOT	0.092***	−0.052***	0.014	0.059***	0.052**	−0.066**
	(0.008)	(0.011)	(0.016)	(0.014)	(0.020)	(0.032)
AGE (/100)	−0.306***	−0.193***		0.231***	0.212***	
	(0.033)	(0.031)		(0.046)	(0.052)	
PATSTOCKGREENEP (/100)	0.051***	0.035***	−0.001			
	(0.004)	(0.004)	(0.003)			
PATSTOCKBROWNEFFEP (/100)				0.102***	0.051***	−0.003
				(0.010)	(0.009)	(0.009)
Observations	27375	24254	19634	27379	19499	11765
Pseudo R2	0.0776	0.317	0.516	0.0990	0.437	0.524
Panel B: Maximum citations						
	GREENCITMAXEP			BROWNEFFCITMAXEP		
LOGS1TOT	−0.100***	−0.208***	−0.055	−0.006	0.070*	0.197*
	(0.024)	(0.054)	(0.071)	(0.018)	(0.037)	(0.114)
AGE (/100)	0.316*	0.659***		0.189	−0.007	
	(0.175)	(0.175)		(0.122)	(0.075)	
PATSTOCKGREENEP (/100)	0.060***	0.064***	−0.019			
	(0.009)	(0.009)	(0.014)			
PATSTOCKBROWNEFFEP (/100)				0.098***	0.085***	0.034**
				(0.010)	(0.012)	(0.017)
Observations	20554	18241	14663	16622	12123	7169
Pseudo R2	0.396	0.665	0.721	0.395	0.693	0.671
Panel C: Blockbuster count						
	GREENCOUNTBBEP			BROWNEFFCOUNTBBEP		
LOGS1TOT	−0.035**	−0.010	−0.028	0.080***	0.103**	−0.025
	(0.014)	(0.031)	(0.034)	(0.020)	(0.043)	(0.056)
AGE (/100)	0.077	0.056		0.566***	0.223***	
	(0.071)	(0.076)		(0.061)	(0.080)	
PATSTOCKGREENEP (/100)	0.099***	0.075***	−0.009			
	(0.006)	(0.006)	(0.007)			
PATSTOCKBROWNEFFEP (/100)				0.150***	0.130***	0.025
				(0.012)	(0.013)	(0.018)
Observations	27222	17382	10089	26792	9218	4949
Pseudo R2	0.314	0.448	0.461	0.331	0.553	0.497
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes

Table B.XIII. Patent Ratio and Firm Type: Splits based on initial firm emissions

The unit of observation is firm-year. The sample period is 2005-2020. We split the Trucost sample with patenting and non-patenting observations into terciles based on firms' initial scope 1 emissions, i.e. the first scope 1 emission we observe. The terciles are calculated within the set of firms entering the sample in a given year. Columns 1 to 3 cover firms with the lowest initial emission tercile, columns 4 to 6 cover firms in the middle group and columns 7 to 9 cover firms in the highest initial emission tercile. The dependent variable is GREENRATIOEP in Panel A and BROWNEFFRATIOEP in Panel B. We include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and MSCI. All variables are defined in Table 3.1 and Table 3.2. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1, 4 and 7 include year and country fixed effects. Columns 2, 5 and 8 include country and Trucost industry-year fixed effects and columns 3, 6 and 9 year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: GREENRATIOEP									
Initial emission tercile:	Lowest			Middle			Highest		
LOGS1TOT	−0.092**	−0.170***	−0.076*	0.046	−0.006	0.005	0.115***	0.014	0.020
	(0.039)	(0.052)	(0.040)	(0.031)	(0.037)	(0.032)	(0.009)	(0.013)	(0.019)
AGE (/100)	−0.622**	−1.254***		−0.234**	−0.083		−0.249***	−0.113***	
	(0.279)	(0.359)		(0.103)	(0.103)		(0.035)	(0.032)	
PATSTOCKGREENEP (/100)	0.682***	0.349***	−0.182**	1.139***	0.949***	−0.456***	0.042***	0.033***	0.002
	(0.090)	(0.115)	(0.079)	(0.089)	(0.132)	(0.093)	(0.004)	(0.004)	(0.003)
Observations	2990	2189	1277	6928	4984	4020	17878	15276	14852
Pseudo R2	0.145	0.286	0.573	0.129	0.369	0.545	0.0983	0.362	0.494
Panel B: BROWNEFFRATIOEP									
Initial emission tercile:	Lowest			Middle			Highest		
LOGS1TOT	0.166	0.430*	0.179	0.062	0.074	−0.007	0.052***	0.042*	−0.087**
	(0.103)	(0.222)	(0.131)	(0.055)	(0.104)	(0.083)	(0.016)	(0.022)	(0.036)
AGE (/100)	−0.994	−1.381		0.159	0.168		0.206***	0.214***	
	(0.790)	(1.356)		(0.159)	(0.218)		(0.048)	(0.051)	
PATSTOCKBROWNEFFEP (/100)	1.176***	3.377**	−0.093	8.219***	8.113***	−2.391***	0.096***	0.042***	0.003
	(0.272)	(1.648)	(0.353)	(1.460)	(2.014)	(0.726)	(0.009)	(0.008)	(0.008)
Observations	2817	963	272	6818	2460	1772	17803	12125	10132
Pseudo R2	0.289	0.749	0.683	0.191	0.497	0.539	0.0788	0.422	0.525
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	no	yes	yes	no	yes	yes	no
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry X Year F.E.	no	yes	no	no	yes	no	no	yes	no
Firm F.E.	no	no	yes	no	no	yes	no	no	yes

Table B.XIV. Patent ratios and Firm-Level Outcomes - Intensive Margin

The unit of observation is firm-year. The sample period is 2005 to 2020. We require firm-year observations to have *at least one* green patent at the EPO in Panel A and one brown efficiency patent at the EPO in Panel B. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 year. In Panel B, the key independent variable similarly is *BROWNEFFRATIOEP*. Controls include: *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. All variables are defined in Table 3.1 and Table 3.2 and lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENRATIOEP	−0.014	−0.011	−0.008	−0.070	−0.019	−0.050	−0.005	0.021	−0.127	−0.119	−0.021	−0.004
	(0.035)	(0.034)	(0.020)	(0.145)	(0.020)	(0.105)	(0.015)	(0.025)	(0.663)	(0.159)	(0.019)	(0.017)
Observations	13226	13226	13224	3868	13226	13226	13226	13226	3868	13226	13226	13225
R2	0.957	0.942	0.978	0.916	0.979	0.940	0.847	0.951	0.889	0.726	0.914	0.979
L3 GREENRATIOEP	−0.003	−0.028	0.001	0.257	0.006	0.116	0.003	0.023	−0.036	−0.131	−0.005	−0.001
	(0.035)	(0.036)	(0.019)	(0.293)	(0.018)	(0.108)	(0.014)	(0.024)	(0.724)	(0.114)	(0.017)	(0.015)
Observations	10830	10830	10830	1514	10830	10830	10830	10830	1514	11718	11718	11714
R2	0.969	0.957	0.984	0.984	0.986	0.965	0.904	0.968	0.986	0.825	0.944	0.986
L5 GREENRATIOEP	−0.044	0.001	0.021		0.013	−0.025	0.004	0.003		0.012	−0.010	0.012
	(0.035)	(0.039)	(0.021)		(0.021)	(0.090)	(0.014)	(0.022)		(0.109)	(0.017)	(0.017)
Observations	8393	8393	8393		8393	8393	8393	8393		9135	9135	9132
R2	0.977	0.965	0.986		0.988	0.979	0.937	0.978		0.884	0.945	0.989
L1 3YEARAVGGREENRATIOEP	−0.027	−0.025	−0.002	−0.100	−0.010	0.009	0.000	0.040	0.058	−0.198	0.018	−0.025
	(0.043)	(0.044)	(0.024)	(0.191)	(0.024)	(0.140)	(0.020)	(0.029)	(0.976)	(0.169)	(0.022)	(0.020)
Observations	16737	16737	16735	5376	16737	16737	16737	16737	5376	16735	16735	16735
R2	0.964	0.950	0.982	0.932	0.983	0.945	0.854	0.958	0.909	0.737	0.932	0.982
Panel B: Brown efficiency innovation												
L1 BROWNEFFRATIOEP	−0.026	0.014	−0.009	0.122	−0.005	0.200	0.015	0.026	2.548	0.069	−0.017	−0.006
	(0.065)	(0.055)	(0.031)	(0.242)	(0.035)	(0.221)	(0.018)	(0.041)	(1.896)	(0.231)	(0.035)	(0.026)
Observations	6167	6167	6167	1629	6167	6167	6167	6167	1629	6167	6167	6166
R2	0.967	0.942	0.977	0.889	0.979	0.939	0.859	0.948	0.859	0.816	0.911	0.979
L3 BROWNEFFRATIOEP	−0.010	0.109*	0.012	−0.082	0.001	−0.250	0.024	0.023	−1.520	−0.109	−0.045	0.012
	(0.049)	(0.056)	(0.027)	(0.317)	(0.030)	(0.202)	(0.018)	(0.031)	(1.540)	(0.199)	(0.028)	(0.022)
Observations	5138	5138	5138	590	5138	5138	5138	5138	590	5443	5443	5442
R2	0.979	0.961	0.984	0.951	0.986	0.964	0.915	0.970	0.981	0.847	0.933	0.988
L5 BROWNEFFRATIOEP	0.026	0.039	0.048		0.037	0.075	−0.021	0.023		0.118	0.058	0.048*
	(0.054)	(0.050)	(0.031)		(0.030)	(0.146)	(0.018)	(0.029)		(0.152)	(0.039)	(0.026)
Observations	4077	4077	4077		4077	4077	4077	4077		4349	4349	4350
R2	0.984	0.970	0.986		0.989	0.982	0.943	0.978		0.896	0.938	0.990
L1 3YEARAVGBROWNEFFRATIOEP	0.050	0.092	0.007	−0.633	0.029	0.295	0.010	0.040	−1.204	−0.192	−0.038	0.020
	(0.067)	(0.069)	(0.034)	(0.465)	(0.042)	(0.319)	(0.024)	(0.048)	(3.088)	(0.277)	(0.033)	(0.030)
Observations	8588	8588	8588	2502	8588	8588	8588	8588	2502	8586	8586	8586
R2	0.976	0.958	0.986	0.938	0.986	0.943	0.876	0.963	0.898	0.795	0.940	0.984
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XV. Patent Count and Firm-Level Outcomes

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENCOUNTEP* lagged by 1, 3, or 5 years as well as a 3-year rolling average lagged by 1 year. In Panel B, the key independent variable similarly is *BROWNEFFCOUNTEP*. Controls include: *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. All variables are defined in Table 3.1 and are lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENCOUNTEP/100	0.041	0.185	0.198**	0.680	0.133*	−0.488**	0.052	−0.372***	11.815**	−1.075**	−0.220***	0.291***
	(0.149)	(0.125)	(0.081)	(0.906)	(0.078)	(0.247)	(0.065)	(0.091)	(4.758)	(0.520)	(0.060)	(0.064)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.918	0.980
L3 GREENCOUNTEP/100	0.068	0.056	0.110	0.003	0.062	−0.222	0.056	−0.257***	2.955	−1.820***	−0.178***	0.140**
	(0.139)	(0.116)	(0.075)	(0.887)	(0.074)	(0.200)	(0.060)	(0.084)	(4.812)	(0.430)	(0.062)	(0.063)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 GREENCOUNTEP/100	−0.066	−0.035	0.091		0.045	−0.257	0.100*	−0.143*		−2.201***	−0.151**	0.081
	(0.128)	(0.108)	(0.072)		(0.069)	(0.177)	(0.057)	(0.076)		(0.408)	(0.063)	(0.065)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.972	0.933	0.981		0.888	0.956	0.989
L1 3YEARAVGGREENCOUNTEP	0.415*	0.737***	0.532***	1.493	0.484***	−0.519	0.200**	−0.743***	10.244	−2.994***	−0.254***	0.672***
	(0.230)	(0.200)	(0.144)	(1.456)	(0.149)	(0.367)	(0.087)	(0.126)	(8.360)	(0.854)	(0.089)	(0.130)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.954	0.945	0.974	0.935	0.975	0.928	0.847	0.965	0.907	0.683	0.911	0.970
Panel B: Brown efficiency innovation												
L1 BROWNEFFCOUNTEP/100	−0.159	−1.141***	−0.204	−1.304	−0.328	−0.929	−0.221	−0.574**	15.398	1.081	−0.416**	−0.052
	(0.376)	(0.393)	(0.199)	(2.060)	(0.207)	(0.891)	(0.161)	(0.248)	(13.115)	(0.966)	(0.186)	(0.164)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.918	0.980
L3 BROWNEFFCOUNTEP/100	−0.126	−0.619*	−0.112	0.114	−0.176	−0.659	−0.017	−0.052	−4.847	0.610	−0.388	−0.191
	(0.376)	(0.373)	(0.203)	(2.928)	(0.220)	(0.755)	(0.142)	(0.218)	(9.072)	(0.866)	(0.240)	(0.165)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 BROWNEFFCOUNTEP/100	−0.118	−0.427	−0.002		−0.153	−0.692	−0.035	0.143		1.169	−0.314	−0.054
	(0.399)	(0.367)	(0.187)		(0.215)	(0.803)	(0.143)	(0.203)		(0.799)	(0.285)	(0.157)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.972	0.933	0.981		0.888	0.956	0.989
L1 3YEARAVGBROWNEFFCOUNTEP	0.066	−1.225*	−0.796**	−1.725	−0.793**	−1.108	−0.080	−2.150***	−7.128	1.485	−1.242***	−0.599*
	(0.652)	(0.664)	(0.388)	(4.363)	(0.384)	(1.406)	(0.265)	(0.432)	(24.206)	(1.828)	(0.291)	(0.352)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.954	0.945	0.974	0.935	0.975	0.928	0.847	0.965	0.907	0.682	0.911	0.970
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XVI. Patent Maximum Citations and Firm Level Outcomes

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENCITMAXEP* lagged by 1, 3, or 5 years. In Panel B, the key independent variable similarly is *BROWNEFFCITMAXEP*. Controls include: *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. All variables are defined in Table 3.1 and Table 3.4 and lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENCITMAXEP/10000	0.074	0.063	0.062*	−0.359***	0.061*	0.011	−0.004	0.019	−0.430	−0.088	0.033	0.045
	(0.063)	(0.057)	(0.036)	(0.060)	(0.035)	(0.035)	(0.012)	(0.023)	(0.401)	(0.117)	(0.027)	(0.030)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.917	0.980
L3 GREENCITMAXEP/10000	0.069	0.055	0.033	−0.162***	0.041	0.042	0.005	0.015	−0.431*	0.048	0.014	0.023
	(0.059)	(0.049)	(0.027)	(0.037)	(0.028)	(0.027)	(0.012)	(0.018)	(0.243)	(0.095)	(0.022)	(0.025)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 GREENCITMAXEP/10000	0.051	0.119**	0.029		0.048	0.051	0.028	0.016		0.159	−0.013	0.023
	(0.076)	(0.058)	(0.035)		(0.035)	(0.032)	(0.017)	(0.021)		(0.132)	(0.016)	(0.037)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.971	0.933	0.981		0.888	0.956	0.989
Panel B: Brown efficiency innovation												
L1 BROWNEFFCITMAXEP/10000	−0.232	0.060	0.547	0.080	0.231	−0.483	−0.287	0.110	14.840	2.153**	−0.089	0.361
	(0.262)	(0.160)	(0.467)	(6.439)	(0.271)	(0.317)	(0.223)	(0.193)	(31.518)	(0.971)	(0.104)	(0.295)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.917	0.980
L3 BROWNEFFCITMAXEP/10000	−0.325**	−0.145	0.516	−1.810	0.164	−0.349	−0.293	−0.015	6.474	2.055***	−0.018	0.356
	(0.157)	(0.134)	(0.403)	(4.749)	(0.180)	(0.259)	(0.206)	(0.128)	(17.012)	(0.760)	(0.068)	(0.234)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 BROWNEFFCITMAXEP/10000	−0.351***	−0.248	0.351		0.015	−0.243	−0.268	−0.024		1.167*	−0.025	0.205
	(0.090)	(0.176)	(0.321)		(0.105)	(0.205)	(0.190)	(0.074)		(0.702)	(0.055)	(0.182)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.971	0.933	0.981		0.888	0.956	0.989
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XVII. Patent blockbuster counts and Firm-Level Outcomes

The unit of observation is firm-year. The sample period is 2005 to 2020. We keep only firms with at least one green blockbuster patent in Panel A and one brown efficiency blockbuster patent in Panel B. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENCOUNTBBEP* lagged by 1, 3, or 5 years. In Panel B, the key independent variable similarly is *BROWNEFFCOUNTBBEP*. Controls include: *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. All variables are defined in Table 3.1 and Table 3.4 and lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENCOUNTBBEP	0.027	0.017	0.030**	−0.095	0.028**	−0.059	0.006	0.017	−0.068	−0.077	0.010	0.027***
	(0.023)	(0.021)	(0.012)	(0.089)	(0.013)	(0.052)	(0.009)	(0.013)	(0.319)	(0.060)	(0.013)	(0.010)
Observations	7435	7435	7435	2275	7435	7435	7435	7435	2275	7435	7435	7435
R2	0.948	0.930	0.974	0.904	0.975	0.923	0.828	0.950	0.917	0.731	0.870	0.974
L3 GREENCOUNTBBEP	−0.002	0.016	0.023**	−0.076	0.020*	−0.042	−0.001	0.025**	−0.138	−0.092*	−0.014	0.015
	(0.021)	(0.019)	(0.011)	(0.094)	(0.012)	(0.036)	(0.008)	(0.012)	(0.295)	(0.050)	(0.013)	(0.010)
Observations	5951	5951	5951	1004	5951	5951	5951	5951	1006	6386	6386	6387
R2	0.962	0.949	0.981	0.975	0.981	0.954	0.889	0.967	0.989	0.814	0.911	0.981
L5 GREENCOUNTBBEP	−0.031	0.010	0.015		0.014	−0.006	−0.000	0.022**		−0.050	−0.020	0.004
	(0.020)	(0.019)	(0.011)		(0.011)	(0.032)	(0.008)	(0.011)		(0.048)	(0.014)	(0.010)
Observations	4504	4504	4504		4504	4504	4504	4504		4967	4967	4969
R2	0.971	0.959	0.982		0.984	0.971	0.928	0.977		0.876	0.919	0.985
Panel B: Brown efficiency innovation												
L1 BROWNEFFCOUNTBBEP	−0.032	−0.009	0.008	0.125	−0.005	−0.096	−0.010	−0.016	0.484	0.174*	0.004	0.018
	(0.030)	(0.027)	(0.014)	(0.140)	(0.015)	(0.066)	(0.012)	(0.016)	(0.732)	(0.104)	(0.014)	(0.012)
Observations	4445	4445	4445	1274	4445	4445	4445	4445	1274	4445	4445	4445
R2	0.945	0.909	0.963	0.864	0.968	0.927	0.825	0.944	0.868	0.778	0.832	0.969
L3 BROWNEFFCOUNTBBEP	0.002	0.011	0.016	−0.041	0.008	−0.103*	−0.016	−0.025	0.469	0.157**	0.009	0.022*
	(0.028)	(0.027)	(0.015)	(0.180)	(0.015)	(0.061)	(0.012)	(0.016)	(0.591)	(0.078)	(0.016)	(0.012)
Observations	3685	3685	3685	568	3685	3685	3685	3685	568	3841	3841	3841
R2	0.961	0.934	0.972	0.941	0.976	0.957	0.888	0.964	0.985	0.831	0.873	0.977
L5 BROWNEFFCOUNTBBEP	0.029	0.026	0.016		0.009	−0.042	−0.011	−0.001		0.160**	−0.014	0.019
	(0.029)	(0.025)	(0.017)		(0.016)	(0.056)	(0.012)	(0.015)		(0.073)	(0.018)	(0.013)
Observations	2941	2941	2941		2941	2941	2941	2941		3100	3100	3100
R2	0.971	0.951	0.976		0.981	0.975	0.928	0.975		0.879	0.893	0.981
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XVIII. Patent ratios and Firm-Level Outcomes - Top Quintile

The unit of observation is firm-year. The sample period is 2005 to 2020. We calculate quintiles based on three 5-year intervals' average patent ratios and keep only the top quintile based on the average GREENRATIOEP in Panel A and based on the average BROWNEFFRATIOEP in Panel B. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year based ratio lagged by 1 year. In Panel B, the key independent variable similarly is *BROWNEFFRATIOEP*. Controls include: *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. All variables are defined in Table 3.1 and Table 3.2 and lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENRATIOEP	0.010	0.001	0.017	0.025	0.006	0.028	−0.019	0.019	0.254	0.028	−0.011	0.012
	(0.034)	(0.035)	(0.021)	(0.097)	(0.022)	(0.087)	(0.014)	(0.024)	(0.548)	(0.159)	(0.020)	(0.018)
Observations	4850	4850	4849	1992	4850	4850	4850	4850	1992	4850	4850	4850
R2	0.976	0.957	0.984	0.935	0.986	0.962	0.886	0.956	0.887	0.677	0.935	0.984
L3 GREENRATIOEP	−0.045	−0.003	0.005	−0.029	−0.009	−0.110	−0.014	−0.008	0.415	−0.064	−0.005	0.006
	(0.027)	(0.029)	(0.018)	(0.094)	(0.016)	(0.087)	(0.012)	(0.022)	(0.563)	(0.105)	(0.018)	(0.014)
Observations	3633	3633	3633	780	3633	3633	3633	3633	780	4042	4042	4042
R2	0.988	0.975	0.991	0.986	0.993	0.978	0.941	0.969	0.985	0.803	0.961	0.991
L5 GREENRATIOEP	−0.010	−0.024	−0.016		−0.018	0.084	−0.001	−0.027		−0.109	−0.017	−0.014
	(0.028)	(0.036)	(0.019)		(0.017)	(0.084)	(0.012)	(0.020)		(0.106)	(0.015)	(0.015)
Observations	2429	2429	2429		2429	2429	2429	2429		2868	2868	2868
R2	0.990	0.975	0.991		0.994	0.983	0.959	0.976		0.851	0.972	0.993
L1 3YEARAVGGREENRATIOEP	−0.026	−0.141***	0.016	−0.113	−0.021	0.164	−0.052***	0.036	−0.311	−0.201	−0.020	−0.018
	(0.043)	(0.047)	(0.024)	(0.168)	(0.026)	(0.153)	(0.018)	(0.029)	(0.846)	(0.183)	(0.024)	(0.021)
Observations	8671	8671	8670	3547	8671	8671	8671	8671	3547	8669	8669	8671
R2	0.973	0.955	0.984	0.936	0.986	0.946	0.888	0.957	0.896	0.704	0.932	0.985
Panel B: Brown efficiency innovation												
L1 BROWNEFFRATIOEP	0.017	−0.021	−0.011	−0.265	−0.020	−0.025	0.014	0.014	0.253	0.037	−0.001	0.001
	(0.041)	(0.039)	(0.019)	(0.171)	(0.021)	(0.127)	(0.012)	(0.024)	(0.989)	(0.153)	(0.023)	(0.016)
Observations	5964	5964	5964	1957	5964	5964	5964	5964	1957	5964	5964	5964
R2	0.971	0.941	0.980	0.849	0.983	0.941	0.885	0.957	0.865	0.799	0.893	0.982
L3 BROWNEFFRATIOEP	−0.002	0.003	0.001	−0.077	−0.008	−0.147	0.023**	0.020	−0.750	0.040	−0.007	0.008
	(0.035)	(0.037)	(0.019)	(0.099)	(0.020)	(0.121)	(0.011)	(0.023)	(0.832)	(0.137)	(0.021)	(0.014)
Observations	4621	4621	4621	790	4621	4621	4621	4621	790	4919	4919	4920
R2	0.984	0.963	0.987	0.947	0.989	0.968	0.943	0.975	0.982	0.846	0.908	0.989
L5 BROWNEFFRATIOEP	−0.016	−0.005	0.001		−0.017	−0.239*	−0.013	−0.007		0.359**	0.025	0.021
	(0.037)	(0.034)	(0.020)		(0.021)	(0.132)	(0.009)	(0.023)		(0.144)	(0.020)	(0.015)
Observations	3249	3249	3249		3249	3249	3249	3249		3544	3544	3546
R2	0.987	0.972	0.988		0.991	0.978	0.966	0.983		0.888	0.909	0.991
L1 3YEARAVGBROWNEFFRATIOEP	0.151***	−0.027	0.012	−0.136	0.028	0.095	0.004	0.024	−1.373	−0.014	−0.005	0.025
	(0.049)	(0.049)	(0.024)	(0.223)	(0.027)	(0.190)	(0.018)	(0.031)	(1.354)	(0.224)	(0.024)	(0.023)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.958	0.951	0.982	0.935	0.982	0.928	0.847	0.965	0.907	0.718	0.923	0.980
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XIX. Patent ratios and Firm-Level Outcomes - OECD env-tech definition

The unit of observation is firm-year. The sample period is 2005 to 2020. We keep all firm-year EPO patenting observations in Panel A and require firm-year observations to have *at least one* OECD env-tech patent at the EPO in Panel B. The dependent variables are logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. The key independent variable is *OECDRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 year. Controls include: *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. All variables are defined in Table 3.1 and Table B.V and lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: All patenting firm-year observations												
L1 OECDRATIOEP	0.026	−0.001	0.004	−0.070	−0.001	−0.068	−0.014	−0.005	0.094	−0.003	0.002	−0.002
	(0.025)	(0.024)	(0.014)	(0.076)	(0.014)	(0.067)	(0.010)	(0.017)	(0.427)	(0.093)	(0.014)	(0.012)
Observations	29585	29585	29584	10349	29585	29585	29585	29585	10349	29578	29578	29580
R2	0.953	0.948	0.980	0.931	0.981	0.922	0.843	0.961	0.898	0.720	0.917	0.980
L3 OECDRATIOEP	0.012	−0.054**	−0.010	0.061	−0.015	−0.047	−0.014	−0.004	−0.286	0.003	−0.001	−0.015
	(0.024)	(0.023)	(0.013)	(0.120)	(0.014)	(0.067)	(0.010)	(0.016)	(0.383)	(0.074)	(0.012)	(0.011)
Observations	22261	22261	22261	4160	22261	22261	22261	22261	4166	25158	25153	25155
R2	0.967	0.962	0.986	0.982	0.986	0.955	0.902	0.974	0.986	0.827	0.945	0.986
L5 OECDRATIOEP	0.010	−0.049**	−0.005		0.002	0.048	−0.006	−0.002		0.041	0.001	−0.010
	(0.026)	(0.024)	(0.015)		(0.015)	(0.072)	(0.010)	(0.016)		(0.072)	(0.011)	(0.012)
Observations	15482	15482	15482		15482	15482	15482	15482		18347	18347	18343
R2	0.973	0.965	0.985		0.986	0.972	0.933	0.981		0.888	0.956	0.989
L1 3YEARAVGOECDRATIOEP	0.006	−0.068**	−0.008	−0.402***	−0.024	−0.040	−0.045***	0.011	−1.096*	0.005	−0.009	−0.028**
	(0.030)	(0.031)	(0.016)	(0.131)	(0.018)	(0.092)	(0.015)	(0.021)	(0.645)	(0.111)	(0.017)	(0.013)
Observations	38221	38221	38220	14552	38221	38221	38221	38221	14552	38210	38210	38214
R2	0.958	0.951	0.982	0.935	0.982	0.928	0.848	0.965	0.907	0.718	0.923	0.980
Panel B: Firm-year observations with at least one OECD env-tech patent												
L1 OECDRATIOEP	−0.037	0.003	−0.006	−0.020	−0.018	−0.217**	−0.009	−0.005	1.003	−0.079	−0.010	−0.006
	(0.036)	(0.035)	(0.019)	(0.169)	(0.019)	(0.106)	(0.015)	(0.025)	(0.802)	(0.144)	(0.019)	(0.015)
Observations	13509	13509	13509	3765	13509	13509	13509	13509	3765	13507	13507	13507
R2	0.957	0.938	0.978	0.889	0.980	0.937	0.854	0.950	0.883	0.751	0.910	0.980
L3 OECDRATIOEP	−0.031	−0.075**	−0.031	0.352	−0.041**	−0.096	−0.018	0.002	0.085	0.114	−0.010	−0.023
	(0.036)	(0.033)	(0.019)	(0.367)	(0.019)	(0.109)	(0.014)	(0.022)	(0.949)	(0.109)	(0.016)	(0.015)
Observations	10978	10978	10978	1350	10978	10978	10978	10978	1350	11868	11868	11863
R2	0.967	0.953	0.982	0.966	0.984	0.960	0.906	0.967	0.985	0.834	0.941	0.986
L5 OECDRATIOEP	0.018	−0.016	0.005		0.021	0.091	−0.000	0.014		0.177*	0.041***	0.004
	(0.034)	(0.034)	(0.020)		(0.019)	(0.086)	(0.014)	(0.020)		(0.099)	(0.015)	(0.016)
Observations	8549	8549	8549		8549	8549	8549	8549		9244	9244	9239
R2	0.975	0.962	0.984		0.987	0.977	0.938	0.979		0.888	0.945	0.988
L1 3YEARAVGOECDRATIOEP	−0.038	−0.007	−0.018	−0.390*	−0.022	−0.101	−0.019	0.015	−0.534	0.053	0.001	−0.038**
	(0.043)	(0.046)	(0.022)	(0.211)	(0.023)	(0.147)	(0.020)	(0.030)	(1.103)	(0.164)	(0.021)	(0.018)
Observations	17197	17197	17197	5343	17197	17197	17197	17197	5343	17191	17191	17194
R2	0.964	0.948	0.983	0.921	0.983	0.941	0.860	0.958	0.906	0.753	0.930	0.983
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XX. Green Patent Citations and GICS-6 Industry-Level Outcomes

The unit of observation is GICS-6 industry-year and the sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry. The key explanatory variables of interest is *AVGGREENCITMAXEP* in Panel A and *AVGBROWNEFFCITMAXEP* in Panel B. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. *AVGGREENCITMAXEP* (*AVGBROWNEFFCITMAXEP*) is an equally weighted average of *GREENCITMAXEP* (*BROWNEFFCITMAXEP*) across all patenting firms in a given year and industry. Other independent variables are calculated as in Table 3.9 and all are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: AVGGREENCITMAXEP on all firms											
L1 AVGGREENCITMAXEP/10000	5.123	4.892	4.110	39.553*	−4.122	−0.161	0.798	64.779	−0.019	3.144	3.893
	(3.432)	(3.822)	(3.263)	(21.481)	(3.514)	(0.714)	(0.993)	(98.512)	(0.013)	(2.898)	(3.330)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.962	0.932	0.960	0.961	0.988	0.733	0.976	0.842	0.911	0.925	0.936
L3 AVGGREENCITMAXEP/10000	1.423	1.331	1.182	9.856	−3.687	−0.131	0.486	−12.823	−0.002	0.728	0.848
	(1.395)	(0.905)	(0.745)	(12.299)	(2.812)	(0.625)	(0.547)	(57.431)	(0.005)	(0.539)	(0.748)
Observations	837	837	837	122	837	837	837	122	837	837	837
R2	0.981	0.978	0.990	0.990	0.994	0.782	0.987	0.973	0.957	0.984	0.986
L5 AVGGREENCITMAXEP/10000	0.408	−0.009	0.068		−1.638	−0.481	0.521		−0.005	−0.413	−0.238
	(1.393)	(0.745)	(0.717)		(2.411)	(0.515)	(0.453)		(0.005)	(0.543)	(0.686)
Observations	708	708	708		708	708	708		708	708	708
R2	0.986	0.985	0.991		0.997	0.852	0.992		0.966	0.984	0.987
Panel A.2: AVGGREENCITMAXEP on ever patenting firms											
L1 AVGGREENCITMAXEP/10000	3.958**	1.105	1.682	44.726*	−4.992	−0.617	1.750	29.369	−0.007	−0.220	0.701
	(2.017)	(1.165)	(1.072)	(23.675)	(5.705)	(0.879)	(1.330)	(67.699)	(0.005)	(0.622)	(0.752)
Observations	974	974	974	261	974	974	974	261	974	974	974
R2	0.962	0.960	0.984	0.954	0.926	0.678	0.973	0.695	0.954	0.979	0.981
L3 AVGGREENCITMAXEP/10000	2.335	1.434	2.016**	−0.455	−4.844	−0.210	1.411**	20.383	−0.009	0.234	0.956
	(1.471)	(0.975)	(0.897)	(10.797)	(3.849)	(0.715)	(0.685)	(67.914)	(0.006)	(0.526)	(0.807)
Observations	834	834	834	122	834	834	834	122	834	834	834
R2	0.976	0.973	0.988	0.986	0.952	0.740	0.984	0.936	0.967	0.982	0.986
L5 AVGGREENCITMAXEP/10000	2.058	0.999	0.887		0.758	−0.757	1.454*		−0.006	0.660	−0.041
	(2.072)	(1.142)	(1.134)		(4.697)	(0.939)	(0.804)		(0.005)	(0.851)	(1.066)
Observations	705	705	705		705	705	705		705	705	705
R2	0.982	0.982	0.991		0.970	0.824	0.989		0.975	0.986	0.988
Panel A.3: AVGGREENCITMAXEP on never patenting firms											
L1 AVGGREENCITMAXEP/10000	−2.829	−1.218	1.181	26.779	−3.186	−1.131	0.942	32.742	−0.016	−1.487	0.968
	(3.842)	(2.707)	(2.239)	(16.749)	(7.748)	(0.910)	(3.654)	(60.013)	(0.060)	(2.685)	(2.282)
Observations	964	964	964	261	964	964	964	261	964	964	964
R2	0.941	0.921	0.940	0.972	0.979	0.735	0.629	0.959	0.794	0.938	0.939
L3 AVGGREENCITMAXEP/10000	−1.541	0.786	0.123	17.597**	−11.922	−0.626	−4.898	−73.881	−0.054	−1.657	0.850
	(2.217)	(1.994)	(1.892)	(8.022)	(8.273)	(0.750)	(4.933)	(55.735)	(0.054)	(2.604)	(1.900)
Observations	819	819	819	122	819	819	819	122	819	819	819
R2	0.960	0.948	0.961	0.998	0.993	0.846	0.860	0.996	0.825	0.958	0.960
L5 AVGGREENCITMAXEP/10000	0.435	1.864	0.326		−7.476	−0.350	−3.978		−0.050	−1.153	1.055
	(2.699)	(1.514)	(1.541)		(6.280)	(0.583)	(3.570)		(0.035)	(1.274)	(1.449)
Observations	685	685	685		685	685	685		685	685	685
R2	0.973	0.959	0.967		0.996	0.898	0.930		0.867	0.963	0.966
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: AVGBROWNEFFCITMAXEP on all firms											
L1 AVGBROWNEFFCITMAXEP/10000	−0.627	1.283	0.008	33.930	−5.533	−1.974	2.777	345.615	−0.003	−1.345	−1.608
	(3.144)	(2.345)	(1.559)	(27.867)	(15.384)	(2.748)	(3.220)	(277.515)	(0.016)	(1.795)	(1.848)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.962	0.932	0.959	0.961	0.988	0.734	0.976	0.842	0.911	0.924	0.936
L3 AVGBROWNEFFCITMAXEP/10000	1.339	−0.487	−1.414	3.126	−0.590	−2.252	2.272	104.580	−0.000	−1.735	−2.450
	(4.042)	(2.095)	(1.835)	(21.317)	(10.820)	(2.475)	(2.248)	(91.126)	(0.017)	(2.094)	(2.327)
Observations	837	837	837	122	837	837	837	122	837	837	837
R2	0.981	0.978	0.990	0.990	0.994	0.783	0.988	0.973	0.957	0.984	0.986
L5 AVGBROWNEFFCITMAXEP/10000	2.844	−1.244	−1.812		4.477	−2.424	1.212		0.010	−0.909	−2.374
	(3.131)	(1.625)	(1.636)		(8.864)	(2.154)	(1.614)		(0.014)	(1.894)	(1.946)
Observations	708	708	708		708	708	708		708	708	708
R2	0.986	0.985	0.991		0.997	0.852	0.992		0.966	0.984	0.987
Panel B.2: AVGBROWNEFFCITMAXEP on ever patenting firms											
L1 AVGBROWNEFFCITMAXEP/10000	−2.115	0.854	0.667	39.204	−8.492	−2.598	2.820	578.806	0.005	−0.001	−2.477
	(3.535)	(2.816)	(2.352)	(35.840)	(19.671)	(3.220)	(3.205)	(523.196)	(0.009)	(1.794)	(2.469)
Observations	974	974	974	261	974	974	974	261	974	974	974
R2	0.962	0.960	0.984	0.954	0.926	0.678	0.973	0.696	0.954	0.979	0.981
L3 AVGBROWNEFFCITMAXEP/10000	−3.180	−2.018	−1.865	2.681	−1.737	−2.786	1.329	159.525	0.007	−0.770	−3.681
	(4.460)	(3.181)	(2.021)	(24.839)	(13.421)	(2.979)	(1.873)	(188.949)	(0.010)	(1.912)	(2.677)
Observations	834	834	834	122	834	834	834	122	834	834	834
R2	0.976	0.973	0.988	0.986	0.952	0.740	0.984	0.936	0.967	0.982	0.986
L5 AVGBROWNEFFCITMAXEP/10000	−1.055	−1.739	−3.017*		−8.655	−2.763	−0.123		0.011	0.440	−3.389*
	(4.369)	(2.391)	(1.702)		(9.582)	(2.494)	(1.349)		(0.009)	(1.264)	(1.975)
Observations	705	705	705		705	705	705		705	705	705
R2	0.982	0.982	0.991		0.970	0.824	0.989		0.975	0.986	0.988
Panel B.3: AVGBROWNEFFCITMAXEP on never patenting firms											
L1 AVGBROWNEFFCITMAXEP/10000	5.938	−1.590	−3.651	24.852	39.698	−2.262	0.140	92.524	−0.170**	−2.435	−2.796
	(5.709)	(3.318)	(2.622)	(45.298)	(30.177)	(2.037)	(9.520)	(95.387)	(0.079)	(4.001)	(2.027)
Observations	964	964	964	261	964	964	964	261	964	964	964
R2	0.941	0.921	0.940	0.972	0.980	0.734	0.629	0.959	0.795	0.938	0.939
L3 AVGBROWNEFFCITMAXEP/10000	12.857	4.281	0.254	12.429	46.793	−0.013	21.218	13.544	−0.155	−2.026	−0.795
	(9.586)	(4.864)	(3.691)	(10.184)	(30.469)	(2.023)	(23.349)	(57.324)	(0.096)	(3.160)	(1.729)
Observations	819	819	819	122	819	819	819	122	819	819	819
R2	0.960	0.948	0.961	0.998	0.993	0.846	0.861	0.996	0.825	0.958	0.960
L5 AVGBROWNEFFCITMAXEP/10000	13.582*	4.420	1.351		32.154	−0.508	16.545		−0.100	−1.056	0.310
	(7.300)	(3.423)	(2.355)		(19.834)	(1.564)	(15.338)		(0.070)	(2.530)	(1.485)
Observations	685	685	685		685	685	685		685	685	685
R2	0.973	0.959	0.967		0.996	0.898	0.930		0.867	0.963	0.966
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXI. OECD Patent Ratios and GICS-6 Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A dependent variables are calculated across all firms within the given industry. In Panel B dependent variables are calculated across all ever patenting firms within the given industry and in Panel C dependent variables are calculated across all never patenting firms within the given industry. The key explanatory variables of interest is *OECDRATIOEP*. Controls include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are calculated as in Table 3.9 and B.XX and are lagged by 1, 3 or 5 years respectivley. All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: OECDRATIOEP on all firms											
L1 OECDRATIOEP	−0.107	0.064	−0.145*	0.412	0.858	0.145*	−0.033	7.304	0.001*	0.013	−0.129*
	(0.135)	(0.143)	(0.075)	(0.646)	(0.963)	(0.085)	(0.098)	(6.108)	(0.001)	(0.052)	(0.066)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.962	0.932	0.960	0.961	0.988	0.734	0.976	0.843	0.911	0.924	0.936
L3 OECDRATIOEP	0.074	0.033	−0.129*	−0.253	−0.074	0.228**	−0.177*	5.215	0.001**	−0.012	−0.075
	(0.135)	(0.117)	(0.070)	(1.100)	(0.895)	(0.104)	(0.101)	(7.600)	(0.001)	(0.049)	(0.063)
Observations	837	837	837	122	837	837	837	122	837	837	837
R2	0.981	0.978	0.990	0.990	0.994	0.784	0.988	0.974	0.957	0.984	0.986
L5 OECDRATIOEP	0.197*	0.077	−0.063		0.734	0.229*	−0.045		0.001	−0.034	−0.051
	(0.116)	(0.092)	(0.064)		(0.531)	(0.138)	(0.080)		(0.000)	(0.042)	(0.058)
Observations	708	708	708		708	708	708		708	708	708
R2	0.986	0.985	0.991		0.997	0.853	0.992		0.966	0.984	0.987
L1 3YEARAVGOECDRATIOEP	0.152	0.219	−0.077	−0.452	1.273	0.385***	−0.169	10.101	0.001	0.115	−0.030
	(0.205)	(0.189)	(0.111)	(0.957)	(1.425)	(0.133)	(0.111)	(10.754)	(0.001)	(0.103)	(0.101)
Observations	988	988	988	267	988	988	988	267	988	988	988
R2	0.962	0.931	0.960	0.967	0.988	0.734	0.976	0.843	0.903	0.914	0.937
Panel B: OECDRATIOEP on ever patenting firms											
L1 OECDRATIOEP	−0.348	−0.088	−0.180**	1.228	2.249	0.136	0.060	14.481	0.002***	0.067	−0.191**
	(0.229)	(0.204)	(0.079)	(0.864)	(2.305)	(0.114)	(0.092)	(11.915)	(0.001)	(0.063)	(0.075)
Observations	974	974	974	261	974	974	974	261	974	974	974
R2	0.962	0.960	0.984	0.954	0.926	0.679	0.973	0.700	0.955	0.979	0.981
L3 OECDRATIOEP	−0.319*	−0.083	−0.143*	0.733	0.792	0.253*	−0.099	5.961	0.001***	0.041	−0.116
	(0.187)	(0.165)	(0.073)	(1.052)	(1.594)	(0.134)	(0.062)	(9.004)	(0.001)	(0.064)	(0.072)
Observations	834	834	834	122	834	834	834	122	834	834	834
R2	0.976	0.973	0.988	0.986	0.952	0.741	0.984	0.936	0.967	0.982	0.986
L5 OECDRATIOEP	−0.136	−0.126	−0.180**		2.301	0.199	−0.053		0.001***	−0.007	−0.153*
	(0.213)	(0.157)	(0.083)		(1.402)	(0.184)	(0.074)		(0.000)	(0.054)	(0.080)
Observations	705	705	705		705	705	705		705	705	705
R2	0.982	0.982	0.991		0.971	0.824	0.989		0.976	0.986	0.988
L1 3YEARAVGOECDRATIOEP	−0.423	−0.030	−0.111	0.672	3.345	0.372*	−0.012	21.939	0.002***	0.185	−0.109
	(0.312)	(0.288)	(0.121)	(1.324)	(3.332)	(0.195)	(0.125)	(23.179)	(0.001)	(0.114)	(0.118)
Observations	985	985	985	265	985	985	985	265	985	985	985
R2	0.963	0.961	0.984	0.956	0.927	0.682	0.973	0.697	0.950	0.979	0.982
Panel C: OECDRATIOEP on never patenting firms											
L1 OECDRATIOEP	−0.113	0.127	−0.102	0.390	0.765	0.179**	−0.157	−0.424	0.001	0.014	−0.065
	(0.143)	(0.136)	(0.087)	(0.671)	(0.909)	(0.074)	(0.177)	(3.490)	(0.001)	(0.060)	(0.079)
Observations	964	964	964	261	964	964	964	261	964	964	964
R2	0.941	0.921	0.940	0.972	0.980	0.735	0.629	0.959	0.794	0.938	0.939
L3 OECDRATIOEP	0.089	−0.007	−0.081	0.573	0.527	0.152*	−0.227	2.739	0.001	0.010	−0.016
	(0.127)	(0.113)	(0.085)	(0.541)	(0.892)	(0.084)	(0.147)	(2.920)	(0.001)	(0.067)	(0.077)
Observations	819	819	819	122	819	819	819	122	819	819	819
R2	0.960	0.948	0.961	0.998	0.993	0.847	0.860	0.996	0.824	0.958	0.960
L5 OECDRATIOEP	0.108	0.041	−0.019		0.761	0.156**	−0.055		0.000	−0.066	−0.002
	(0.111)	(0.104)	(0.084)		(0.523)	(0.075)	(0.106)		(0.001)	(0.072)	(0.082)
Observations	685	685	685		685	685	685		685	685	685
R2	0.973	0.959	0.967		0.996	0.899	0.929		0.866	0.963	0.966
L1 3YEARAVGOECDRATIOEP	0.073	0.063	−0.102	−0.044	2.193	0.259**	−0.417	−1.584	0.001	0.052	−0.015
	(0.253)	(0.215)	(0.145)	(0.860)	(1.430)	(0.105)	(0.304)	(4.042)	(0.002)	(0.105)	(0.124)
Observations	976	976	976	267	976	976	976	267	976	976	976
R2	0.941	0.920	0.939	0.974	0.979	0.735	0.631	0.959	0.793	0.932	0.937
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXII. Patent Ratios and Trucost Industry-Level Outcomes

The unit of observation is Trucost industry-year and the sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years for the Trucost sample. In Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry. The key explanatory variables of interest are *GREENRATIOEP* and in Panel A and *BROWNEFFRATIOEP* in Panel B. Controls include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either industry level logs of sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the given industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation											
Panel A.1: GREENRATIOEP on all firms											
L1 GREENRATIOEP	−0.067	0.017	−0.032	0.092	0.157	0.046	−0.241***	0.266	−0.001	−0.039	0.009
	(0.071)	(0.073)	(0.055)	(0.133)	(0.437)	(0.136)	(0.083)	(1.606)	(0.001)	(0.054)	(0.052)
Observations	4486	4486	4486	1343	4486	4486	4486	1343	4486	4486	4486
R2	0.939	0.923	0.943	0.951	0.873	0.565	0.880	0.860	0.764	0.942	0.950
L3 GREENRATIOEP	−0.051	0.033	−0.043	−0.020	0.164	0.172*	−0.068	−1.347	−0.001	−0.046	−0.032
	(0.076)	(0.077)	(0.062)	(.)	(0.431)	(0.096)	(0.059)	(.)	(0.001)	(0.053)	(0.058)
Observations	3745	3745	3745	644	3745	3745	3745	644	3745	3745	3745
R2	0.959	0.943	0.954	0.992	0.947	0.731	0.978	0.988	0.848	0.956	0.960
L5 GREENRATIOEP	0.046	0.057	0.005		0.290	0.082	0.002		−0.001	−0.004	−0.006
	(0.081)	(0.074)	(0.068)		(0.362)	(0.052)	(0.049)		(0.001)	(0.054)	(0.063)
Observations	3030	3030	3030		3030	3030	3030		3030	3030	3030
R2	0.971	0.959	0.965		0.965	0.847	0.985		0.890	0.967	0.970
L1 3YEARAVGGREENRATIOEP	−0.036	0.103	−0.012	0.358	0.661	0.207**	−0.213**	−6.362	−0.003**	−0.013	0.035
	(0.089)	(0.098)	(0.071)	(0.224)	(0.513)	(0.100)	(0.098)	(5.112)	(0.001)	(0.055)	(0.066)
Observations	4861	4861	4861	1458	4861	4861	4861	1458	4861	4861	4861
R2	0.936	0.921	0.939	0.950	0.874	0.569	0.886	0.931	0.763	0.935	0.945
Panel A.2: GREENRATIOEP on ever patenting firms											
L1 GREENRATIOEP	0.032	0.092	−0.018	0.508**	0.418	0.025	−0.279	0.925	−0.002*	−0.044	0.030
	(0.107)	(0.106)	(0.079)	(0.224)	(0.593)	(0.285)	(0.171)	(2.559)	(0.001)	(0.067)	(0.072)
Observations	4459	4459	4459	1337	4459	4459	4459	1337	4459	4459	4459
R2	0.923	0.905	0.930	0.919	0.384	0.304	0.822	0.798	0.769	0.904	0.937
L3 GREENRATIOEP	−0.154	−0.029	−0.119	0.275	0.258	0.264	−0.134	−2.049	0.000	−0.049	−0.076
	(0.101)	(0.099)	(0.081)	(.)	(0.405)	(0.173)	(0.085)	(.)	(0.001)	(0.065)	(0.073)
Observations	3702	3702	3702	640	3702	3702	3702	640	3702	3702	3702
R2	0.949	0.932	0.946	0.990	0.923	0.560	0.969	0.983	0.851	0.936	0.951
L5 GREENRATIOEP	0.005	0.025	−0.033		0.214	0.126	−0.089		−0.000	−0.017	−0.025
	(0.096)	(0.087)	(0.076)		(0.268)	(0.078)	(0.087)		(0.001)	(0.058)	(0.070)
Observations	2982	2982	2982		2982	2982	2982		2982	2982	2982
R2	0.965	0.952	0.961		0.955	0.749	0.980		0.883	0.955	0.964
L1 3YEARAVGGREENRATIOEP	−0.012	0.192	−0.084	1.164**	1.143	0.343*	−0.358*	−1.764	−0.002	−0.070	0.003
	(0.151)	(0.151)	(0.112)	(0.469)	(0.716)	(0.177)	(0.213)	(3.907)	(0.002)	(0.082)	(0.101)
Observations	4778	4778	4778	1426	4778	4778	4778	1426	4778	4778	4778
R2	0.917	0.901	0.924	0.920	0.412	0.306	0.830	0.879	0.754	0.901	0.929
Panel A.3: GREENRATIOEP on never patenting firms											
L1 GREENRATIOEP	−0.105	0.001	−0.083	−0.144	0.240	0.029	−0.151	−1.772	−0.000	−0.017	−0.046
	(0.098)	(0.093)	(0.066)	(0.175)	(0.627)	(0.080)	(0.134)	(2.021)	(0.002)	(0.065)	(0.063)
Observations	3112	3112	3112	1226	3112	3112	3112	1226	3112	3112	3112
R2	0.927	0.910	0.931	0.949	0.642	0.656	0.331	0.895	0.622	0.910	0.940
L3 GREENRATIOEP	−0.080	0.025	−0.048	−0.083	−0.075	0.139**	−0.074	−0.484	−0.002	−0.095	−0.034
	(0.094)	(0.092)	(0.074)	(0.081)	(0.509)	(0.062)	(0.111)	(1.423)	(0.001)	(0.060)	(0.073)
Observations	2396	2396	2396	576	2396	2396	2396	576	2396	2396	2396
R2	0.949	0.931	0.942	0.994	0.972	0.840	0.994	0.991	0.713	0.931	0.946
L5 GREENRATIOEP	−0.061	−0.051	−0.030		−0.231	−0.007	0.101		−0.000	−0.026	−0.022
	(0.109)	(0.102)	(0.080)		(0.506)	(0.063)	(0.094)		(0.001)	(0.060)	(0.080)
Observations	1736	1736	1736		1736	1736	1736		1736	1736	1736
R2	0.959	0.941	0.950		0.980	0.897	0.986		0.775	0.947	0.953
L1 3YEARAVGGREENRATIOEP	−0.137	0.123	0.008	−0.349	−0.336	0.131*	−0.083	−7.870**	−0.006***	−0.102	0.019
	(0.116)	(0.111)	(0.083)	(0.299)	(0.517)	(0.071)	(0.163)	(3.776)	(0.002)	(0.072)	(0.079)
Observations	3402	3402	3402	1331	3402	3402	3402	1331	3402	3402	3402
R2	0.925	0.906	0.927	0.945	0.647	0.658	0.336	0.945	0.623	0.908	0.936
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Brown efficiency innovation											
Panel B.1: BROWNEFFRATIOEP on all firms											
L1 BROWNEFFRATIOEP	−0.377**	−0.438***	−0.221*	−0.020	−1.322	−0.111	0.005	−7.431	0.003	−0.046	−0.193*
	(0.185)	(0.139)	(0.119)	(0.341)	(1.011)	(0.075)	(0.190)	(7.885)	(0.002)	(0.102)	(0.109)
Observations	4486	4486	4486	1343	4486	4486	4486	1343	4486	4486	4486
R2	0.939	0.923	0.943	0.951	0.873	0.565	0.880	0.860	0.764	0.942	0.950
L3 BROWNEFFRATIOEP	−0.145	−0.245*	−0.120	−0.242	−1.512	−0.018	−0.092	6.606	0.002	0.005	−0.089
	(0.158)	(0.137)	(0.127)	(.)	(0.946)	(0.065)	(0.128)	(.)	(0.002)	(0.091)	(0.121)
Observations	3745	3745	3745	644	3745	3745	3745	644	3745	3745	3745
R2	0.959	0.943	0.954	0.992	0.947	0.731	0.978	0.988	0.848	0.956	0.960
L5 BROWNEFFRATIOEP	−0.090	−0.160	−0.039		−0.547	0.008	−0.020		0.003*	0.049	−0.035
	(0.146)	(0.135)	(0.123)		(0.733)	(0.050)	(0.083)		(0.002)	(0.100)	(0.123)
Observations	3030	3030	3030		3030	3030	3030		3030	3030	3030
R2	0.971	0.959	0.965		0.965	0.847	0.985		0.890	0.967	0.970
L1 3YEARAVGBROWNEFFRATIOEP	−0.367	−0.474***	−0.305**	0.002	−2.244*	−0.057	−0.168	26.777	0.001	−0.063	−0.231*
	(0.230)	(0.183)	(0.145)	(0.524)	(1.307)	(0.088)	(0.145)	(16.300)	(0.003)	(0.110)	(0.128)
Observations	4861	4861	4861	1458	4861	4861	4861	1458	4861	4861	4861
R2	0.936	0.922	0.939	0.950	0.874	0.569	0.886	0.931	0.763	0.935	0.945
Panel B.2: BROWNEFFRATIOEP on ever patenting firms											
L1 BROWNEFFRATIOEP	−0.254	−0.424***	−0.050	0.164	−0.420	−0.321***	0.113	−1.371	0.004	0.039	−0.049
	(0.182)	(0.160)	(0.135)	(0.464)	(1.004)	(0.117)	(0.141)	(8.440)	(0.003)	(0.113)	(0.125)
Observations	4459	4459	4459	1337	4459	4459	4459	1337	4459	4459	4459
R2	0.923	0.906	0.930	0.919	0.384	0.304	0.822	0.798	0.769	0.904	0.937
L3 BROWNEFFRATIOEP	−0.096	−0.278*	−0.024	−0.377	−0.539	−0.162	−0.076	−2.798	0.004**	0.028	−0.004
	(0.149)	(0.145)	(0.124)	(.)	(0.553)	(0.108)	(0.067)	(.)	(0.002)	(0.103)	(0.119)
Observations	3702	3702	3702	640	3702	3702	3702	640	3702	3702	3702
R2	0.949	0.932	0.946	0.990	0.923	0.559	0.969	0.983	0.851	0.936	0.951
L5 BROWNEFFRATIOEP	−0.105	−0.190	0.010		−0.130	−0.019	0.046		0.004**	0.097	−0.005
	(0.143)	(0.137)	(0.125)		(0.470)	(0.075)	(0.067)		(0.002)	(0.107)	(0.121)
Observations	2982	2982	2982		2982	2982	2982		2982	2982	2982
R2	0.965	0.952	0.961		0.955	0.749	0.980		0.883	0.955	0.964
L1 3YEARAVGBROWNEFFRATIOEP	−0.177	−0.486**	−0.155	−0.180	−0.995	−0.365**	−0.165	−0.177	0.005*	0.043	−0.064
	(0.231)	(0.247)	(0.162)	(0.870)	(1.340)	(0.149)	(0.142)	(23.636)	(0.003)	(0.131)	(0.139)
Observations	4778	4778	4778	1426	4778	4778	4778	1426	4778	4778	4778
R2	0.917	0.901	0.924	0.920	0.412	0.305	0.830	0.879	0.754	0.901	0.929
Panel B.3: BROWNEFFRATIOEP on never patenting firms											
L1 BROWNEFFRATIOEP	0.152	−0.049	−0.195*	−0.568*	2.221	0.287	−0.088	−15.837*	0.002	−0.071	−0.177
	(0.258)	(0.179)	(0.113)	(0.330)	(1.442)	(0.194)	(0.397)	(9.223)	(0.005)	(0.123)	(0.119)
Observations	3112	3112	3112	1226	3112	3112	3112	1226	3112	3112	3112
R2	0.927	0.910	0.931	0.949	0.642	0.656	0.331	0.896	0.623	0.910	0.940
L3 BROWNEFFRATIOEP	−0.044	−0.094	−0.045	0.016	0.179	−0.061	0.025	12.087*	−0.001	−0.003	−0.017
	(0.257)	(0.210)	(0.182)	(0.123)	(1.248)	(0.157)	(0.414)	(6.709)	(0.003)	(0.126)	(0.183)
Observations	2396	2396	2396	576	2396	2396	2396	576	2396	2396	2396
R2	0.949	0.931	0.942	0.994	0.972	0.840	0.994	0.991	0.713	0.931	0.946
L5 BROWNEFFRATIOEP	0.283	0.085	0.087		0.909	−0.097	−0.164		0.000	0.084	0.084
	(0.173)	(0.182)	(0.155)		(1.029)	(0.130)	(0.189)		(0.002)	(0.091)	(0.154)
Observations	1736	1736	1736		1736	1736	1736		1736	1736	1736
R2	0.959	0.941	0.950		0.980	0.897	0.986		0.775	0.947	0.953
L1 3YEARAVGBROWNEFFRATIOEP	−0.102	−0.188	−0.396***	0.252	2.241	0.218	0.147	20.808	0.002	−0.248	−0.414***
	(0.255)	(0.213)	(0.143)	(0.455)	(1.682)	(0.215)	(0.586)	(13.606)	(0.004)	(0.162)	(0.146)
Observations	3402	3402	3402	1331	3402	3402	3402	1331	3402	3402	3402
R2	0.925	0.906	0.927	0.945	0.647	0.658	0.336	0.945	0.622	0.908	0.936
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXIII. Green Patent Ratios in North America and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in North America. In Panel B, dependent variables are calculated across all firms with their headquarter outside of North America. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in North America. The key explanatory variables of interest is *GREENRATIOEP*. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: NA-firm based GREENRATIOEP On NA firms											
Panel A.1: And all firms											
L1 GREENRATIOEP	−0.046	−0.168	−0.057	0.292	−1.364	−0.082	−0.005	3.808**	−0.000	−0.008	−0.066
	(0.138)	(0.181)	(0.087)	(0.411)	(1.326)	(0.071)	(0.127)	(1.870)	(0.001)	(0.061)	(0.063)
Observations	861	861	861	233	861	861	861	233	861	861	861
R2	0.958	0.934	0.974	0.958	0.962	0.910	0.968	0.919	0.924	0.959	0.975
L3 GREENRATIOEP	−0.022	−0.046	−0.049	−0.181	0.418	−0.067	0.009	−1.454	0.000	−0.046	−0.047
	(0.146)	(0.127)	(0.091)	(0.404)	(1.527)	(0.070)	(0.095)	(2.739)	(0.001)	(0.065)	(0.066)
Observations	737	737	737	108	737	737	737	108	737	737	737
R2	0.963	0.964	0.978	0.997	0.970	0.952	0.985	0.995	0.923	0.964	0.979
L5 GREENRATIOEP	0.077	−0.019	0.023		0.794	−0.092	0.067		0.000	−0.019	0.009
	(0.146)	(0.101)	(0.088)		(1.486)	(0.065)	(0.088)		(0.000)	(0.069)	(0.064)
Observations	616	616	616		616	616	616		616	616	616
R2	0.967	0.972	0.980		0.978	0.969	0.990		0.921	0.968	0.979
L1 3YEARAVGGREENRATIOEP	0.018	−0.311	−0.075	−1.948*	1.791	−0.220*	−0.041	−14.001	−0.000	0.023	−0.074
	(0.181)	(0.321)	(0.120)	(1.145)	(1.927)	(0.113)	(0.177)	(12.980)	(0.001)	(0.071)	(0.094)
Observations	907	907	907	255	907	907	907	255	907	907	907
R2	0.959	0.939	0.975	0.960	0.961	0.910	0.967	0.907	0.929	0.957	0.975
Panel A.2: And ever-patenting firms											
L1 GREENRATIOEP	0.001	−0.039	−0.085	0.728	0.146	0.013	0.006	3.554	0.000	−0.008	−0.097
	(0.135)	(0.304)	(0.076)	(0.474)	(2.735)	(0.117)	(0.164)	(2.958)	(0.001)	(0.067)	(0.063)
Observations	861	861	861	233	861	861	861	233	861	861	861
R2	0.948	0.917	0.975	0.941	0.930	0.878	0.961	0.876	0.916	0.943	0.975
L3 GREENRATIOEP	−0.060	−0.143	−0.111	0.270	1.020	−0.037	−0.007	3.512	0.000	−0.038	−0.102
	(0.148)	(0.274)	(0.078)	(0.749)	(2.037)	(0.123)	(0.104)	(3.750)	(0.001)	(0.076)	(0.063)
Observations	737	737	737	108	737	737	737	108	737	737	737
R2	0.955	0.936	0.978	0.995	0.963	0.922	0.981	0.994	0.913	0.953	0.978
L5 GREENRATIOEP	0.044	−0.130	−0.045		1.574	−0.062	−0.032		−0.000	−0.076	−0.025
	(0.137)	(0.220)	(0.068)		(1.450)	(0.110)	(0.091)		(0.001)	(0.089)	(0.056)
Observations	616	616	616		616	616	616		616	616	616
R2	0.961	0.955	0.980		0.978	0.948	0.988		0.929	0.963	0.979
L1 3YEARAVGGREENRATIOEP	−0.030	0.035	−0.130	−1.774	−1.291	−0.246*	−0.292	−23.729	−0.001	0.063	−0.048
	(0.209)	(0.464)	(0.123)	(1.459)	(5.802)	(0.149)	(0.246)	(20.617)	(0.001)	(0.091)	(0.106)
Observations	907	907	907	255	907	907	907	255	907	907	907
R2	0.945	0.927	0.977	0.946	0.928	0.879	0.961	0.845	0.909	0.948	0.977
Panel A.3: And never-patenting firms											
L1 GREENRATIOEP	0.033	−0.210	0.122	0.059	−4.563	−0.041	0.182	2.641	0.000	−0.003	0.094
	(0.173)	(0.264)	(0.149)	(0.451)	(3.853)	(0.125)	(0.255)	(2.204)	(0.002)	(0.113)	(0.130)
Observations	696	696	696	233	696	696	696	233	696	695	696
R2	0.942	0.884	0.925	0.967	0.854	0.804	0.908	0.962	0.771	0.888	0.916
L3 GREENRATIOEP	0.178	0.240	0.202	−0.431	−1.754	0.030	0.229	−6.160**	−0.001	−0.055	0.131
	(0.181)	(0.171)	(0.150)	(0.280)	(4.574)	(0.068)	(0.275)	(2.384)	(0.001)	(0.108)	(0.130)
Observations	557	557	557	108	557	557	557	108	557	557	557
R2	0.964	0.937	0.954	0.999	0.894	0.888	0.959	0.999	0.885	0.944	0.949
L5 GREENRATIOEP	0.078	0.103	0.171		1.513	0.019	0.414		0.001	−0.038	0.050
	(0.167)	(0.169)	(0.148)		(3.916)	(0.063)	(0.268)		(0.001)	(0.107)	(0.117)
Observations	426	426	426		426	426	426		426	426	426
R2	0.976	0.966	0.969		0.931	0.942	0.970		0.931	0.963	0.968
L1 3YEARAVGGREENRATIOEP	0.415*	−0.190	0.388*	−0.885	4.226	0.042	0.349	−4.551	−0.000	0.121	0.261
	(0.234)	(0.437)	(0.210)	(0.998)	(6.175)	(0.127)	(0.402)	(4.916)	(0.002)	(0.163)	(0.200)
Observations	738	738	738	255	738	738	738	255	738	737	738
R2	0.944	0.883	0.923	0.967	0.822	0.803	0.904	0.955	0.773	0.888	0.913
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: NA-firm based GREENRATIOEP On Non-NA firms											
Panel B.1: And all firms											
L1 GREENRATIOEP	−0.162	0.004	−0.197**	0.083	−2.534	0.730	−0.517***	1.083	0.001	0.039	−0.045
	(0.103)	(0.191)	(0.085)	(0.421)	(1.908)	(0.533)	(0.141)	(2.726)	(0.001)	(0.049)	(0.083)
Observations	863	863	863	233	863	863	863	233	863	863	863
R2	0.967	0.951	0.968	0.958	0.985	0.715	0.968	0.807	0.934	0.936	0.950
L3 GREENRATIOEP	−0.041	−0.052	−0.042	−0.772	−1.915	0.479	−0.226*	−4.179	0.000	0.026	−0.005
	(0.099)	(0.182)	(0.078)	(0.612)	(1.609)	(0.353)	(0.136)	(4.187)	(0.001)	(0.046)	(0.072)
Observations	740	740	740	108	740	740	740	108	740	740	740
R2	0.985	0.978	0.990	0.987	0.993	0.754	0.982	0.966	0.940	0.982	0.984
L5 GREENRATIOEP	−0.000	−0.010	−0.041		0.549	0.564	−0.112		0.000	0.005	0.003
	(0.089)	(0.164)	(0.078)		(0.693)	(0.487)	(0.143)		(0.000)	(0.047)	(0.067)
Observations	619	619	619		619	619	619		619	619	619
R2	0.989	0.984	0.992		0.997	0.834	0.989		0.951	0.982	0.986
L1 3YEARAVGGREENRATIOEP	−0.229	−0.211	−0.258*	−1.003	−4.702	1.260*	−0.530***	−4.315	0.001	0.071	−0.138
	(0.185)	(0.331)	(0.148)	(0.637)	(3.342)	(0.647)	(0.189)	(3.307)	(0.001)	(0.088)	(0.143)
Observations	910	910	910	257	910	910	910	257	910	910	910
R2	0.968	0.949	0.968	0.964	0.986	0.721	0.967	0.808	0.930	0.926	0.950
Panel B.2: And ever-patenting firms											
L1 GREENRATIOEP	−0.326**	−0.075	−0.237**	0.638	−2.021	0.911	−0.435***	1.460	0.000	−0.065	−0.093
	(0.146)	(0.199)	(0.105)	(0.619)	(1.926)	(0.672)	(0.132)	(3.095)	(0.001)	(0.055)	(0.116)
Observations	855	855	855	233	855	855	855	233	855	855	855
R2	0.969	0.965	0.982	0.950	0.933	0.663	0.964	0.644	0.947	0.976	0.974
L3 GREENRATIOEP	−0.369**	−0.095	−0.177*	−1.582	−1.107	0.593	−0.148	−5.855	0.000	−0.132**	−0.123
	(0.179)	(0.189)	(0.101)	(1.111)	(2.418)	(0.395)	(0.142)	(4.896)	(0.001)	(0.064)	(0.112)
Observations	731	731	731	108	731	731	731	108	731	731	731
R2	0.976	0.973	0.985	0.981	0.937	0.708	0.975	0.922	0.951	0.980	0.977
L5 GREENRATIOEP	−0.271	−0.088	−0.247**		2.258	0.705	−0.056		0.000	−0.173***	−0.209*
	(0.174)	(0.179)	(0.104)		(1.959)	(0.576)	(0.172)		(0.001)	(0.062)	(0.108)
Observations	609	609	609		609	609	609		609	609	609
R2	0.980	0.979	0.987		0.952	0.803	0.983		0.966	0.981	0.979
L1 3YEARAVGGREENRATIOEP	−0.985***	−0.273	−0.522***	−1.224	−4.592	1.653**	−0.471*	−4.645	0.000	−0.224**	−0.348
	(0.309)	(0.324)	(0.199)	(0.781)	(3.385)	(0.796)	(0.246)	(4.056)	(0.001)	(0.110)	(0.214)
Observations	900	900	900	254	900	900	900	254	900	900	900
R2	0.964	0.959	0.977	0.954	0.906	0.675	0.955	0.656	0.938	0.965	0.966
Panel B.3: And never-patenting firms											
L1 GREENRATIOEP	−0.075	0.122	0.003	0.063	−2.467	0.204	−0.950	2.999	0.001	0.129*	0.112
	(0.121)	(0.218)	(0.097)	(0.321)	(3.269)	(0.248)	(0.589)	(2.324)	(0.001)	(0.074)	(0.086)
Observations	845	845	845	233	845	845	845	233	845	845	845
R2	0.944	0.937	0.952	0.972	0.949	0.702	0.449	0.972	0.796	0.939	0.954
L3 GREENRATIOEP	−0.043	−0.093	0.065	0.107	−2.647	0.216	−0.321	−1.809	0.001	0.125	0.098
	(0.114)	(0.191)	(0.093)	(0.317)	(2.565)	(0.295)	(0.202)	(2.069)	(0.001)	(0.077)	(0.080)
Observations	717	717	717	108	717	717	717	108	717	717	717
R2	0.961	0.959	0.970	0.998	0.981	0.824	0.752	0.997	0.820	0.955	0.969
L5 GREENRATIOEP	−0.016	−0.085	0.071		−1.138	0.233	−0.010		0.001	0.079	0.072
	(0.113)	(0.156)	(0.101)		(1.669)	(0.247)	(0.220)		(0.001)	(0.088)	(0.088)
Observations	593	593	593		593	593	593		593	593	593
R2	0.973	0.970	0.977		0.990	0.882	0.857		0.845	0.961	0.973
L1 3YEARAVGGREENRATIOEP	−0.208	−0.068	0.117	−0.322	−10.059*	0.299	−0.888	−0.152	0.001	0.234**	0.140
	(0.181)	(0.377)	(0.151)	(0.453)	(5.467)	(0.340)	(0.563)	(2.332)	(0.002)	(0.104)	(0.136)
Observations	891	891	891	257	891	891	891	257	891	891	891
R2	0.946	0.935	0.953	0.974	0.954	0.696	0.455	0.968	0.797	0.934	0.953
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXIV. Brown Efficiency Patent Ratios in North America and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in North America. In Panel B, dependent variables are calculated across all firms with their headquarter outside of North America. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in North America. The key explanatory variables of interest is *BROWNEFFRATIOEP*. Controls include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: NA-firm based BROWNEFFRATIOEP On NA firms											
Panel A.1: And all firms											
L1 BROWNEFFRATIOEP	0.124	0.086	0.216	−0.992	4.714**	0.071	0.456**	−4.241	0.001	−0.046	0.067
	(0.226)	(0.410)	(0.131)	(1.213)	(2.274)	(0.120)	(0.223)	(5.090)	(0.001)	(0.112)	(0.085)
Observations	861	861	861	233	861	861	861	233	861	861	861
R2	0.958	0.934	0.974	0.958	0.963	0.909	0.968	0.918	0.924	0.959	0.975
L3 BROWNEFFRATIOEP	−0.087	0.025	0.035	0.807	0.109	0.077	0.047	5.496	0.001	0.010	0.041
	(0.213)	(0.200)	(0.124)	(0.805)	(2.466)	(0.086)	(0.154)	(3.746)	(0.001)	(0.095)	(0.075)
Observations	737	737	737	108	737	737	737	108	737	737	737
R2	0.963	0.964	0.978	0.997	0.970	0.951	0.985	0.995	0.923	0.964	0.979
L5 BROWNEFFRATIOEP	−0.410*	−0.037	−0.200		−2.194	0.103	−0.189		0.000	−0.054	−0.064
	(0.212)	(0.160)	(0.134)		(2.762)	(0.097)	(0.162)		(0.001)	(0.117)	(0.090)
Observations	616	616	616		616	616	616		616	616	616
R2	0.967	0.972	0.980		0.979	0.969	0.990		0.921	0.968	0.979
L1 3YEARAVGBROWNEFFRATIOEP	−0.089	0.190	0.152	−2.331	−1.126	0.217	0.302	−9.378	0.001	−0.175	0.089
	(0.292)	(0.479)	(0.204)	(2.104)	(3.342)	(0.168)	(0.342)	(12.702)	(0.001)	(0.128)	(0.133)
Observations	907	907	907	255	907	907	907	255	907	907	907
R2	0.959	0.939	0.975	0.959	0.961	0.909	0.967	0.903	0.929	0.958	0.975
Panel A.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	−0.041	0.224	0.129	0.364	5.783	0.137	0.465*	5.776	0.001*	−0.062	−0.007
	(0.199)	(0.653)	(0.110)	(0.978)	(6.409)	(0.188)	(0.276)	(8.275)	(0.001)	(0.097)	(0.089)
Observations	861	861	861	233	861	861	861	233	861	861	861
R2	0.948	0.917	0.975	0.940	0.932	0.878	0.962	0.875	0.916	0.943	0.975
L3 BROWNEFFRATIOEP	−0.202	−0.063	−0.033	2.669	1.707	0.099	0.028	7.051	0.001*	−0.021	−0.013
	(0.205)	(0.458)	(0.098)	(1.948)	(3.445)	(0.161)	(0.148)	(4.818)	(0.001)	(0.078)	(0.067)
Observations	737	737	737	108	737	737	737	108	737	737	737
R2	0.955	0.936	0.978	0.995	0.964	0.923	0.981	0.994	0.913	0.953	0.978
L5 BROWNEFFRATIOEP	−0.549***	−0.069	−0.250**		−1.263	0.172	−0.133		0.001**	−0.032	−0.132*
	(0.208)	(0.357)	(0.107)		(2.395)	(0.181)	(0.148)		(0.001)	(0.079)	(0.070)
Observations	616	616	616		616	616	616		616	616	616
R2	0.961	0.955	0.981		0.977	0.948	0.988		0.929	0.963	0.979
L1 3YEARAVGBROWNEFFRATIOEP	−0.530	−0.441	0.029	−0.996	13.335	0.349	0.592	−12.710	0.001	−0.206*	−0.079
	(0.441)	(0.913)	(0.193)	(2.159)	(11.931)	(0.259)	(0.441)	(21.131)	(0.002)	(0.118)	(0.135)
Observations	907	907	907	255	907	907	907	255	907	907	907
R2	0.945	0.928	0.977	0.945	0.933	0.878	0.961	0.836	0.909	0.948	0.977
Panel A.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	0.434	0.119	0.366	−0.091	8.692	−0.145	0.307	−0.672	−0.004**	−0.047	0.258
	(0.298)	(0.510)	(0.238)	(1.495)	(9.226)	(0.175)	(0.375)	(4.111)	(0.002)	(0.218)	(0.245)
Observations	696	696	696	233	696	696	696	233	696	695	696
R2	0.942	0.884	0.925	0.967	0.855	0.804	0.908	0.961	0.772	0.888	0.916
L3 BROWNEFFRATIOEP	0.294	0.093	0.196	0.088	0.355	0.005	−0.106	9.683**	−0.003	0.091	0.247
	(0.239)	(0.311)	(0.210)	(0.861)	(9.156)	(0.137)	(0.291)	(3.981)	(0.002)	(0.154)	(0.204)
Observations	557	557	557	108	557	557	557	108	557	557	557
R2	0.964	0.937	0.954	0.998	0.894	0.888	0.959	0.998	0.886	0.944	0.949
L5 BROWNEFFRATIOEP	−0.067	−0.143	−0.138		−5.613	−0.073	−0.419*		−0.002*	−0.125	0.010
	(0.259)	(0.295)	(0.234)		(8.455)	(0.110)	(0.248)		(0.001)	(0.194)	(0.198)
Observations	426	426	426		426	426	426		426	426	426
R2	0.976	0.966	0.969		0.933	0.942	0.970		0.932	0.963	0.968
L1 3YEARAVGBROWNEFFRATIOEP	0.261	0.467	0.449	−1.276	−16.281	−0.062	−0.336	−2.625	−0.004	−0.008	0.595*
	(0.386)	(0.561)	(0.305)	(2.178)	(11.656)	(0.164)	(0.521)	(6.986)	(0.003)	(0.302)	(0.323)
Observations	738	738	738	255	738	738	738	255	738	737	738
R2	0.944	0.883	0.923	0.967	0.826	0.803	0.904	0.955	0.773	0.888	0.914
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: NA-firm based BROWNEFFRATIOEP On Non-NA firms											
Panel B.1: And all firms											
L1 BROWNEFFRATIOEP	0.092	−0.058	0.132	−1.443	6.233	−0.133	0.366	−10.327	−0.001	0.017	0.007
	(0.107)	(0.312)	(0.121)	(1.221)	(4.410)	(0.089)	(0.255)	(9.043)	(0.001)	(0.071)	(0.095)
Observations	863	863	863	233	863	863	863	233	863	863	863
R2	0.967	0.951	0.968	0.958	0.986	0.703	0.967	0.808	0.934	0.936	0.950
L3 BROWNEFFRATIOEP	0.199**	−0.047	0.171	4.328	4.893	−0.120	0.212	18.206	−0.000	0.063	0.094
	(0.096)	(0.278)	(0.116)	(2.666)	(3.026)	(0.077)	(0.218)	(15.748)	(0.001)	(0.060)	(0.088)
Observations	740	740	740	108	740	740	740	108	740	740	740
R2	0.985	0.978	0.990	0.988	0.993	0.749	0.982	0.967	0.940	0.982	0.984
L5 BROWNEFFRATIOEP	0.254**	0.163	0.194*		−1.241	−0.080	−0.206		0.000	0.170**	0.210**
	(0.116)	(0.226)	(0.107)		(1.566)	(0.080)	(0.166)		(0.001)	(0.071)	(0.090)
Observations	619	619	619		619	619	619		619	619	619
R2	0.989	0.984	0.992		0.997	0.825	0.989		0.951	0.983	0.986
L1 3YEARAVGBROWNEFFRATIOEP	0.256	−0.437	0.141	1.676	15.149**	−0.204	0.187	20.710	−0.001	0.063	0.070
	(0.171)	(0.435)	(0.167)	(1.612)	(6.084)	(0.146)	(0.341)	(14.639)	(0.001)	(0.122)	(0.148)
Observations	910	910	910	257	910	910	910	257	910	910	910
R2	0.968	0.949	0.968	0.964	0.988	0.703	0.966	0.810	0.930	0.926	0.950
Panel B.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	0.270	0.069	0.202	−4.139**	3.537	−0.130	0.369*	−15.405	0.000	0.133	0.036
	(0.175)	(0.309)	(0.192)	(1.994)	(4.694)	(0.104)	(0.205)	(13.999)	(0.001)	(0.093)	(0.210)
Observations	855	855	855	233	855	855	855	233	855	855	855
R2	0.969	0.965	0.982	0.952	0.933	0.647	0.963	0.646	0.947	0.976	0.974
L3 BROWNEFFRATIOEP	0.429***	−0.026	0.232**	3.772	2.542	−0.167*	0.207	22.021	−0.000	0.169*	0.140
	(0.157)	(0.267)	(0.113)	(2.546)	(4.711)	(0.093)	(0.177)	(19.141)	(0.001)	(0.102)	(0.146)
Observations	731	731	731	108	731	731	731	108	731	731	731
R2	0.976	0.973	0.985	0.981	0.938	0.701	0.975	0.923	0.951	0.980	0.977
L5 BROWNEFFRATIOEP	0.301	0.136	0.339***		−5.066	−0.160	−0.257		−0.000	0.220**	0.416***
	(0.204)	(0.178)	(0.102)		(3.780)	(0.100)	(0.173)		(0.001)	(0.088)	(0.118)
Observations	609	609	609		609	609	609		609	609	609
R2	0.980	0.979	0.987		0.954	0.791	0.983		0.966	0.981	0.979
L1 3YEARAVGBROWNEFFRATIOEP	0.771***	−0.441	0.255	−0.211	13.340**	−0.228	0.421	34.788	−0.001	0.216	0.040
	(0.295)	(0.453)	(0.282)	(2.755)	(6.456)	(0.178)	(0.355)	(22.755)	(0.001)	(0.202)	(0.333)
Observations	900	900	900	254	900	900	900	254	900	900	900
R2	0.963	0.959	0.977	0.954	0.912	0.647	0.955	0.659	0.938	0.965	0.965
Panel B.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	0.001	0.170	−0.037	−1.487*	2.857	−0.153	−0.427	−10.906*	−0.002	−0.031	−0.020
	(0.173)	(0.389)	(0.147)	(0.780)	(7.796)	(0.194)	(0.804)	(6.564)	(0.002)	(0.099)	(0.126)
Observations	845	845	845	233	845	845	845	233	845	845	845
R2	0.944	0.937	0.952	0.973	0.949	0.702	0.448	0.972	0.796	0.939	0.954
L3 BROWNEFFRATIOEP	−0.007	0.110	−0.056	0.824	5.600	0.067	−0.178	1.804	−0.000	−0.012	−0.077
	(0.177)	(0.331)	(0.152)	(0.944)	(4.852)	(0.102)	(0.479)	(7.106)	(0.002)	(0.095)	(0.127)
Observations	717	717	717	108	717	717	717	108	717	717	717
R2	0.961	0.959	0.970	0.998	0.982	0.823	0.752	0.997	0.820	0.955	0.969
L5 BROWNEFFRATIOEP	−0.099	0.152	−0.176		2.529	0.055	−0.539		0.003	0.053	−0.075
	(0.212)	(0.273)	(0.172)		(3.111)	(0.113)	(0.487)		(0.003)	(0.127)	(0.144)
Observations	593	593	593		593	593	593		593	593	593
R2	0.973	0.970	0.977		0.990	0.880	0.857		0.845	0.961	0.973
L1 3YEARAVGBROWNEFFRATIOEP	0.097	0.102	−0.152	0.808	22.034**	0.112	−1.164	3.081	0.002	−0.035	−0.153
	(0.285)	(0.611)	(0.235)	(1.056)	(11.014)	(0.218)	(1.749)	(7.716)	(0.004)	(0.151)	(0.170)
Observations	891	891	891	257	891	891	891	257	891	891	891
R2	0.946	0.935	0.953	0.974	0.956	0.695	0.454	0.968	0.797	0.934	0.953
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXV. Green Patent Ratios in Europe and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in Europe. In Panel B, dependent variables are calculated across all firms with their headquarter outside of Europe. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in Europe. The key explanatory variables of interest is *GREENRATIOEP*. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: EU-firm based GREENRATIOEP On EU firms											
Panel A.1: And all firms											
L1 GREENRATIOEP	0.415**	0.102	0.141	0.149	1.753	−0.035	−0.173	−2.930	0.000	0.175*	0.170
	(0.177)	(0.216)	(0.141)	(0.534)	(1.896)	(0.102)	(0.157)	(4.169)	(0.001)	(0.098)	(0.152)
Observations	887	887	887	241	887	887	887	241	887	887	887
R2	0.961	0.941	0.965	0.950	0.931	0.909	0.922	0.867	0.946	0.924	0.955
L3 GREENRATIOEP	0.356***	0.094	0.169	−0.057	0.315	0.017	−0.129	−0.060	0.001	0.153*	0.219
	(0.133)	(0.189)	(0.134)	(0.301)	(1.208)	(0.041)	(0.081)	(0.918)	(0.001)	(0.090)	(0.139)
Observations	757	757	757	114	757	757	757	114	757	757	757
R2	0.978	0.967	0.983	0.988	0.971	0.953	0.947	0.993	0.946	0.968	0.977
L5 GREENRATIOEP	0.081	0.039	0.079		−0.585	0.008	−0.066		−0.000	0.066	0.113
	(0.114)	(0.126)	(0.103)		(0.757)	(0.032)	(0.077)		(0.001)	(0.066)	(0.104)
Observations	634	634	634		634	634	634		634	634	634
R2	0.986	0.980	0.987		0.988	0.972	0.960		0.952	0.976	0.982
L1 3YEARAVGGREENRATIOEP	0.601***	0.105	0.276*	0.453	4.197*	0.004	−0.014	−0.490	0.001	0.215*	0.244
	(0.202)	(0.248)	(0.164)	(1.413)	(2.358)	(0.093)	(0.191)	(6.282)	(0.001)	(0.119)	(0.172)
Observations	924	924	924	252	924	924	924	252	924	924	924
R2	0.960	0.938	0.963	0.948	0.933	0.907	0.921	0.870	0.945	0.921	0.953
Panel A.2: And ever-patenting firms											
L1 GREENRATIOEP	0.262	0.150	0.124	−0.021	−1.819	−0.050	−0.323	−1.889	−0.000	0.195**	0.183
	(0.241)	(0.233)	(0.154)	(0.676)	(3.187)	(0.152)	(0.256)	(4.032)	(0.002)	(0.095)	(0.174)
Observations	884	884	884	241	884	884	884	241	884	884	884
R2	0.957	0.947	0.970	0.950	0.835	0.876	0.891	0.868	0.902	0.948	0.964
L3 GREENRATIOEP	0.350*	0.117	0.224	−0.194	−0.326	0.033	−0.157*	−0.616	0.000	0.129	0.268
	(0.186)	(0.204)	(0.156)	(0.328)	(2.042)	(0.049)	(0.086)	(1.104)	(0.001)	(0.094)	(0.165)
Observations	751	751	751	114	751	751	751	114	751	751	751
R2	0.974	0.966	0.982	0.986	0.926	0.944	0.936	0.993	0.935	0.964	0.975
L5 GREENRATIOEP	0.060	−0.026	0.065		0.363	−0.007	−0.104		−0.000	0.006	0.125
	(0.187)	(0.138)	(0.125)		(1.803)	(0.036)	(0.080)		(0.001)	(0.084)	(0.125)
Observations	628	628	628		628	628	628		628	628	628
R2	0.982	0.979	0.987		0.956	0.966	0.952		0.958	0.972	0.981
L1 3YEARAVGGREENRATIOEP	0.374	0.033	0.221	0.611	−1.220	−0.013	−0.231	3.091	0.001	0.101	0.212
	(0.272)	(0.300)	(0.149)	(1.859)	(3.826)	(0.142)	(0.288)	(6.455)	(0.002)	(0.141)	(0.180)
Observations	917	917	917	252	917	917	917	252	917	917	917
R2	0.955	0.942	0.971	0.949	0.828	0.873	0.891	0.870	0.902	0.943	0.963
Panel A.3: And never-patenting firms											
L1 GREENRATIOEP	0.198	−0.325	0.159	0.297	5.213	0.063	0.004	2.382	0.001	0.062	0.126
	(0.749)	(0.366)	(0.382)	(0.507)	(7.713)	(0.145)	(0.221)	(2.376)	(0.003)	(0.163)	(0.266)
Observations	756	756	756	217	756	756	756	217	756	754	756
R2	0.889	0.855	0.878	0.964	0.780	0.697	0.908	0.875	0.725	0.881	0.899
L3 GREENRATIOEP	−0.083	0.300	0.038	0.065	3.235	0.133	−0.021	0.264	0.003	0.273	0.094
	(0.688)	(0.373)	(0.244)	(0.274)	(7.664)	(0.100)	(0.199)	(1.553)	(0.003)	(0.177)	(0.177)
Observations	614	614	614	96	614	614	614	96	614	614	614
R2	0.915	0.878	0.900	0.998	0.816	0.817	0.942	0.990	0.833	0.889	0.909
L5 GREENRATIOEP	−0.016	0.195	−0.136		−4.681	0.099	−0.145		0.003	0.147	−0.014
	(0.665)	(0.338)	(0.211)		(7.282)	(0.105)	(0.182)		(0.003)	(0.153)	(0.135)
Observations	494	494	494		494	494	494		494	494	494
R2	0.938	0.915	0.928		0.868	0.868	0.964		0.877	0.940	0.941
L1 3YEARAVGGREENRATIOEP	−0.416	−0.134	−0.292	0.301	6.112	0.247	−0.005	2.937	0.006	0.255	−0.187
	(1.139)	(0.533)	(0.566)	(1.164)	(13.497)	(0.202)	(0.330)	(4.325)	(0.004)	(0.224)	(0.351)
Observations	790	790	790	228	790	790	790	228	790	788	790
R2	0.885	0.854	0.876	0.964	0.763	0.696	0.909	0.874	0.728	0.880	0.898
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: EU-firm based GREENRATIOEP On Non-EU firms											
Panel B.1: And all firms											
L1 GREENRATIOEP	−0.038	0.180	−0.060	0.103	1.573	0.028	−0.002	−6.386	0.000	−0.015	−0.053
	(0.145)	(0.160)	(0.061)	(0.536)	(1.246)	(0.097)	(0.132)	(9.593)	(0.000)	(0.038)	(0.048)
Observations	888	888	888	241	888	888	888	241	888	888	888
R2	0.955	0.916	0.952	0.959	0.988	0.603	0.976	0.840	0.887	0.923	0.930
L3 GREENRATIOEP	0.074	0.054	−0.019	−2.444*	0.194	0.043	−0.076	−28.824	0.001	0.021	0.004
	(0.126)	(0.114)	(0.060)	(1.317)	(0.583)	(0.091)	(0.128)	(20.879)	(0.000)	(0.033)	(0.044)
Observations	759	759	759	114	759	759	759	114	759	759	759
R2	0.976	0.972	0.989	0.991	0.995	0.651	0.991	0.979	0.960	0.980	0.986
L5 GREENRATIOEP	0.094	0.174*	−0.039		−0.578	0.119	−0.030		0.000	−0.031	−0.033
	(0.119)	(0.097)	(0.059)		(0.511)	(0.100)	(0.082)		(0.000)	(0.037)	(0.044)
Observations	636	636	636		636	636	636		636	636	636
R2	0.982	0.980	0.990		0.997	0.732	0.995		0.969	0.980	0.987
L1 3YEARAVGGREENRATIOEP	−0.061	0.319	0.004	−0.363	1.260	0.131	−0.031	−2.040	0.001	0.056	0.013
	(0.168)	(0.229)	(0.090)	(1.267)	(1.660)	(0.110)	(0.167)	(11.719)	(0.001)	(0.066)	(0.073)
Observations	926	926	926	254	926	926	926	254	926	926	926
R2	0.955	0.917	0.953	0.962	0.989	0.603	0.976	0.837	0.873	0.920	0.931
Panel B.2: And ever-patenting firms											
L1 GREENRATIOEP	−0.050	0.037	−0.003	0.636	2.647	0.002	0.120	−12.975	0.000	−0.080	−0.063
	(0.147)	(0.212)	(0.070)	(0.873)	(2.958)	(0.133)	(0.089)	(16.256)	(0.000)	(0.058)	(0.069)
Observations	879	879	879	241	879	879	879	241	879	879	879
R2	0.973	0.945	0.990	0.951	0.939	0.515	0.980	0.672	0.963	0.976	0.987
L3 GREENRATIOEP	0.051	0.144	−0.023	−4.516***	0.110	0.167	−0.002	−82.719**	0.000	−0.074	−0.041
	(0.151)	(0.208)	(0.076)	(1.282)	(1.650)	(0.141)	(0.057)	(32.811)	(0.000)	(0.055)	(0.068)
Observations	749	749	749	114	749	749	749	114	749	749	749
R2	0.978	0.958	0.990	0.990	0.977	0.565	0.991	0.967	0.964	0.978	0.988
L5 GREENRATIOEP	0.134	0.192	−0.056		−0.462	0.183	0.012		−0.000	−0.093*	−0.065
	(0.148)	(0.160)	(0.061)		(1.066)	(0.127)	(0.043)		(0.000)	(0.056)	(0.057)
Observations	626	626	626		626	626	626		626	626	626
R2	0.982	0.972	0.991		0.990	0.648	0.995		0.968	0.981	0.990
L1 3YEARAVGGREENRATIOEP	−0.178	−0.019	−0.030	1.287	3.484	0.164	0.175	−5.809	0.001	−0.125	−0.109
	(0.222)	(0.328)	(0.107)	(2.169)	(4.455)	(0.178)	(0.154)	(21.070)	(0.001)	(0.084)	(0.102)
Observations	916	916	916	252	916	916	916	252	916	916	916
R2	0.969	0.943	0.989	0.946	0.944	0.520	0.980	0.668	0.955	0.977	0.987
Panel B.3: And never-patenting firms											
L1 GREENRATIOEP	−0.112	0.250	−0.069	−0.046	1.795	0.135	0.058	1.962	−0.001	−0.120*	−0.086
	(0.154)	(0.177)	(0.100)	(0.402)	(1.348)	(0.085)	(0.189)	(2.190)	(0.001)	(0.065)	(0.085)
Observations	867	867	867	241	867	867	867	241	867	867	867
R2	0.932	0.911	0.933	0.969	0.972	0.690	0.584	0.961	0.788	0.922	0.932
L3 GREENRATIOEP	0.002	0.017	−0.031	0.131	−0.136	0.052	−0.004	0.442	0.000	−0.008	−0.048
	(0.146)	(0.141)	(0.105)	(0.451)	(0.635)	(0.061)	(0.177)	(2.921)	(0.001)	(0.070)	(0.090)
Observations	726	726	726	114	726	726	726	114	726	726	726
R2	0.951	0.945	0.960	0.998	0.989	0.814	0.839	0.996	0.832	0.950	0.960
L5 GREENRATIOEP	−0.042	−0.018	−0.089		−0.813	0.081	0.001		0.001	−0.056	−0.102
	(0.136)	(0.136)	(0.097)		(0.625)	(0.075)	(0.137)		(0.001)	(0.067)	(0.083)
Observations	593	593	593		593	593	593		593	593	593
R2	0.966	0.960	0.966		0.995	0.875	0.922		0.889	0.953	0.967
L1 3YEARAVGGREENRATIOEP	−0.021	0.560**	0.080	−0.510	0.410	0.214**	−0.012	4.372	0.000	−0.037	0.042
	(0.177)	(0.237)	(0.142)	(1.129)	(1.810)	(0.091)	(0.226)	(4.600)	(0.002)	(0.103)	(0.123)
Observations	905	905	905	254	905	905	905	254	905	905	905
R2	0.932	0.912	0.933	0.972	0.974	0.691	0.591	0.961	0.786	0.917	0.931
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXVI. Brown Efficiency Patent Ratios in Europe and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in Europe. In Panel B, dependent variables are calculated across all firms with their headquarter outside of Europe. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in Europe. The key explanatory variables of interest is *BROWNEFFRATIOEP*. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI*. Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: EU-firm based BROWNEFFRATIOEP On EU firms											
Panel A.1: And all firms											
L1 BROWNEFFRATIOEP	−1.129***	−0.624***	−0.549**	−5.308**	−1.399	0.091	−0.077	−2.971	−0.001	−0.407***	−0.452**
	(0.338)	(0.227)	(0.270)	(2.276)	(0.950)	(0.101)	(0.232)	(15.640)	(0.001)	(0.115)	(0.215)
Observations	887	887	887	241	887	887	887	241	887	887	887
R2	0.962	0.941	0.965	0.951	0.931	0.909	0.922	0.867	0.946	0.924	0.955
L3 BROWNEFFRATIOEP	−0.679***	−0.207	−0.170*	−0.161	−1.382**	0.071	−0.067	7.416	0.000	−0.127	−0.087
	(0.238)	(0.175)	(0.094)	(2.372)	(0.624)	(0.079)	(0.182)	(9.685)	(0.001)	(0.088)	(0.084)
Observations	757	757	757	114	757	757	757	114	757	757	757
R2	0.978	0.967	0.983	0.988	0.971	0.953	0.947	0.993	0.945	0.967	0.977
L5 BROWNEFFRATIOEP	−0.420*	−0.157	−0.160*		−0.443	0.008	−0.284		0.001	0.153*	−0.010
	(0.221)	(0.121)	(0.090)		(0.595)	(0.058)	(0.223)		(0.001)	(0.087)	(0.102)
Observations	634	634	634		634	634	634		634	634	634
R2	0.986	0.980	0.987		0.988	0.972	0.960		0.952	0.976	0.982
L1 3YEARAVGBROWNEFFRATIOEP	−1.764***	−0.540	−0.686	−0.762	−3.214**	0.188	−0.505	10.431	0.000	−0.259	−0.253
	(0.537)	(0.495)	(0.434)	(3.481)	(1.441)	(0.127)	(0.411)	(26.899)	(0.003)	(0.236)	(0.400)
Observations	924	924	924	252	924	924	924	252	924	924	924
R2	0.960	0.938	0.963	0.948	0.931	0.907	0.921	0.870	0.945	0.921	0.952
Panel A.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	−0.940***	−0.341	−0.340	−5.034**	0.049	0.112	0.089	−2.971	−0.001	−0.047	−0.324
	(0.313)	(0.267)	(0.262)	(2.209)	(1.135)	(0.104)	(0.252)	(15.815)	(0.001)	(0.096)	(0.227)
Observations	884	884	884	241	884	884	884	241	884	884	884
R2	0.958	0.947	0.970	0.951	0.834	0.876	0.891	0.868	0.902	0.948	0.964
L3 BROWNEFFRATIOEP	−0.631**	−0.142	−0.085	1.637	−0.259	0.083	−0.042	0.717	−0.000	0.083	−0.022
	(0.252)	(0.213)	(0.097)	(2.228)	(0.771)	(0.086)	(0.191)	(8.122)	(0.001)	(0.091)	(0.094)
Observations	751	751	751	114	751	751	751	114	751	751	751
R2	0.974	0.966	0.981	0.986	0.926	0.944	0.935	0.993	0.935	0.964	0.975
L5 BROWNEFFRATIOEP	−0.520**	−0.209	−0.135		−0.162	0.021	−0.189		0.000	0.124	−0.042
	(0.260)	(0.156)	(0.093)		(0.616)	(0.066)	(0.214)		(0.001)	(0.118)	(0.107)
Observations	628	628	628		628	628	628		628	628	628
R2	0.982	0.979	0.987		0.956	0.966	0.952		0.958	0.972	0.981
L1 3YEARAVGBROWNEFFRATIOEP	−1.585***	−0.036	−0.138	1.155	−2.138	0.231	−0.086	12.825	−0.002	0.278	0.036
	(0.558)	(0.539)	(0.449)	(4.517)	(1.349)	(0.145)	(0.474)	(29.626)	(0.002)	(0.216)	(0.400)
Observations	917	917	917	252	917	917	917	252	917	917	917
R2	0.955	0.942	0.971	0.949	0.828	0.873	0.891	0.871	0.902	0.943	0.963
Panel A.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	−0.402	−0.296	−0.263	−4.659*	−2.865	−0.246	0.068	−16.731	0.001	−0.248	−0.288
	(0.516)	(0.628)	(0.393)	(2.560)	(2.221)	(0.253)	(0.203)	(19.783)	(0.007)	(0.280)	(0.358)
Observations	756	756	756	217	756	756	756	217	756	754	756
R2	0.889	0.855	0.878	0.964	0.778	0.698	0.908	0.875	0.725	0.881	0.899
L3 BROWNEFFRATIOEP	0.392	0.396	0.125	−0.142	1.442	0.026	0.290*	7.935	0.010	0.113	0.007
	(0.437)	(0.575)	(0.351)	(2.087)	(2.033)	(0.221)	(0.174)	(19.643)	(0.007)	(0.298)	(0.359)
Observations	614	614	614	96	614	614	614	96	614	614	614
R2	0.915	0.877	0.900	0.998	0.815	0.817	0.942	0.990	0.834	0.888	0.909
L5 BROWNEFFRATIOEP	0.973***	0.551	0.586**		3.259**	−0.166	0.233		−0.003	0.295	0.578**
	(0.357)	(0.431)	(0.282)		(1.656)	(0.148)	(0.160)		(0.004)	(0.238)	(0.291)
Observations	494	494	494		494	494	494		494	494	494
R2	0.939	0.915	0.929		0.866	0.868	0.964		0.876	0.940	0.941
L1 3YEARAVGBROWNEFFRATIOEP	0.951	1.092	0.557	0.083	2.004	−0.186	0.415	−6.119	0.017	0.747	0.572
	(0.971)	(1.205)	(0.760)	(3.851)	(3.538)	(0.434)	(0.373)	(33.942)	(0.011)	(0.608)	(0.714)
Observations	790	790	790	228	790	790	790	228	790	788	790
R2	0.885	0.854	0.876	0.964	0.761	0.695	0.909	0.874	0.728	0.880	0.898
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: EU-firm based BROWNEFFRATIOEP On Non-EU firms											
Panel B.1: And all firms											
L1 BROWNEFFRATIOEP	−0.016	−0.549	−0.169	−3.850**	0.142	−0.350	0.054	−24.655	−0.000	−0.179	−0.080
	(0.247)	(0.388)	(0.236)	(1.627)	(0.871)	(0.451)	(0.114)	(17.004)	(0.001)	(0.175)	(0.205)
Observations	888	888	888	241	888	888	888	241	888	888	888
R2	0.955	0.916	0.952	0.960	0.988	0.603	0.976	0.840	0.887	0.923	0.930
L3 BROWNEFFRATIOEP	−0.013	−0.316	−0.101	2.868	−0.193	0.158	0.094	−11.787	−0.001	−0.091	−0.037
	(0.200)	(0.253)	(0.174)	(2.735)	(0.736)	(0.434)	(0.080)	(14.795)	(0.001)	(0.130)	(0.146)
Observations	759	759	759	114	759	759	759	114	759	759	759
R2	0.976	0.972	0.989	0.990	0.995	0.651	0.991	0.969	0.960	0.980	0.986
L5 BROWNEFFRATIOEP	0.005	−0.290	−0.093		−0.098	0.344	−0.040		−0.001	−0.036	−0.035
	(0.174)	(0.188)	(0.134)		(0.618)	(0.533)	(0.076)		(0.001)	(0.097)	(0.104)
Observations	636	636	636		636	636	636		636	636	636
R2	0.982	0.980	0.990		0.997	0.732	0.995		0.969	0.980	0.987
L1 3YEARAVGBROWNEFFRATIOEP	0.194	−1.057**	−0.453*	−2.313	−0.244	−0.298	0.223	−28.662	0.002	−0.128	−0.381
	(0.448)	(0.445)	(0.260)	(3.815)	(1.474)	(0.437)	(0.195)	(21.357)	(0.003)	(0.223)	(0.252)
Observations	926	926	926	254	926	926	926	254	926	926	926
R2	0.955	0.917	0.953	0.962	0.989	0.603	0.976	0.838	0.873	0.920	0.932
Panel B.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	0.189	−0.574	−0.092	−3.630**	0.291	−0.313	0.097	−20.988	0.000	−0.033	−0.114
	(0.238)	(0.355)	(0.166)	(1.786)	(0.789)	(0.631)	(0.132)	(19.673)	(0.001)	(0.133)	(0.171)
Observations	879	879	879	241	879	879	879	241	879	879	879
R2	0.973	0.945	0.990	0.951	0.938	0.515	0.980	0.668	0.963	0.976	0.987
L3 BROWNEFFRATIOEP	0.444*	−0.324	0.056	−0.444	0.014	0.229	0.156*	−24.582	−0.000	0.063	−0.004
	(0.255)	(0.289)	(0.138)	(2.989)	(0.665)	(0.592)	(0.089)	(20.226)	(0.001)	(0.133)	(0.155)
Observations	749	749	749	114	749	749	749	114	749	749	749
R2	0.978	0.958	0.990	0.987	0.977	0.564	0.991	0.918	0.964	0.978	0.988
L5 BROWNEFFRATIOEP	0.538	−0.150	0.166		0.164	0.494	−0.015		−0.002	0.176	0.156
	(0.327)	(0.284)	(0.174)		(0.539)	(0.765)	(0.079)		(0.001)	(0.165)	(0.162)
Observations	626	626	626		626	626	626		626	626	626
R2	0.982	0.972	0.991		0.990	0.649	0.995		0.968	0.981	0.990
L1 3YEARAVGBROWNEFFRATIOEP	0.833**	−0.868*	−0.121	−5.686	−0.857	−0.447	0.307	−12.975	−0.000	0.010	−0.272
	(0.413)	(0.498)	(0.236)	(3.687)	(1.113)	(0.642)	(0.196)	(31.582)	(0.003)	(0.201)	(0.242)
Observations	916	916	916	252	916	916	916	252	916	916	916
R2	0.969	0.944	0.989	0.946	0.943	0.520	0.980	0.668	0.954	0.976	0.987
Panel B.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	0.425	−0.173	0.153	−6.750***	1.535	−0.365	0.031	−26.138	−0.004	0.062	0.216
	(0.362)	(0.355)	(0.216)	(1.881)	(2.302)	(0.231)	(0.217)	(19.851)	(0.003)	(0.163)	(0.205)
Observations	867	867	867	241	867	867	867	241	867	867	867
R2	0.932	0.911	0.933	0.971	0.972	0.690	0.584	0.962	0.788	0.922	0.932
L3 BROWNEFFRATIOEP	−0.074	−0.233	−0.104	2.660**	1.020	0.116	0.124	11.144	−0.001	−0.074	0.014
	(0.294)	(0.273)	(0.197)	(1.159)	(1.924)	(0.229)	(0.268)	(7.109)	(0.002)	(0.170)	(0.184)
Observations	726	726	726	114	726	726	726	114	726	726	726
R2	0.951	0.945	0.960	0.998	0.989	0.814	0.839	0.996	0.832	0.950	0.960
L5 BROWNEFFRATIOEP	−0.421	−0.520**	−0.459**		0.645	0.123	0.010		0.002	−0.258*	−0.335*
	(0.296)	(0.243)	(0.205)		(1.164)	(0.200)	(0.174)		(0.002)	(0.149)	(0.177)
Observations	593	593	593		593	593	593		593	593	593
R2	0.966	0.960	0.966		0.995	0.875	0.922		0.889	0.953	0.967
L1 3YEARAVGBROWNEFFRATIOEP	0.342	−0.692	−0.120	−1.504	3.401	−0.222	0.217	−36.969	−0.006	0.021	0.067
	(0.529)	(0.443)	(0.337)	(4.967)	(2.152)	(0.235)	(0.343)	(26.568)	(0.004)	(0.265)	(0.317)
Observations	905	905	905	254	905	905	905	254	905	905	905
R2	0.932	0.912	0.933	0.972	0.974	0.690	0.591	0.962	0.786	0.917	0.931
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXVII. Green Patent Ratios in Asia and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums ofS1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in Asia. In Panel B, dependent variables are calculated across all firms with their headquarter outside of Asia. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in Asia. The key explanatory variables of interest is *GREENRATIOEP*. Controls include *LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, MSCI.* Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (GREENRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: ASIA-firm based GREENRATIOEP On Asian firms											
Panel A.1: And all firms											
L1 GREENRATIOEP	0.302**	0.352**	−0.007	1.071*	2.199*	0.031	−0.109	−2.105	0.002	0.052	0.055
	(0.132)	(0.160)	(0.088)	(0.610)	(1.329)	(0.139)	(0.119)	(6.086)	(0.001)	(0.069)	(0.089)
Observations	835	835	835	240	835	835	835	240	835	835	835
R2	0.957	0.933	0.960	0.960	0.981	0.524	0.932	0.806	0.922	0.930	0.950
L3 GREENRATIOEP	0.183	0.251*	0.006	−0.418	−0.824	0.178	−0.193*	−1.742	0.000	0.003	0.069
	(0.129)	(0.134)	(0.078)	(0.809)	(0.687)	(0.136)	(0.110)	(2.169)	(0.001)	(0.060)	(0.073)
Observations	704	704	704	114	704	704	704	114	704	704	704
R2	0.973	0.956	0.981	0.987	0.994	0.567	0.967	0.960	0.940	0.965	0.976
L5 GREENRATIOEP	0.125	0.202	0.021		−0.407	0.183	−0.002		0.000	−0.045	0.025
	(0.124)	(0.136)	(0.077)		(0.823)	(0.163)	(0.126)		(0.001)	(0.070)	(0.076)
Observations	586	586	586		586	586	586		586	586	586
R2	0.978	0.964	0.983		0.997	0.645	0.978		0.949	0.965	0.975
L1 3YEARAVGGREENRATIOEP	0.539**	0.810***	0.098	1.320	0.257	0.331**	−0.276*	−2.279	−0.000	0.175	0.210
	(0.221)	(0.244)	(0.146)	(1.102)	(1.416)	(0.159)	(0.145)	(10.147)	(0.002)	(0.114)	(0.145)
Observations	878	878	878	255	878	878	878	255	878	878	878
R2	0.957	0.936	0.960	0.966	0.978	0.529	0.933	0.807	0.907	0.920	0.950
Panel A.2: And ever-patenting firms											
L1 GREENRATIOEP	0.529**	0.156	−0.038	1.603*	−1.329	−0.055	−0.245	0.777	0.003	0.121	0.058
	(0.266)	(0.211)	(0.128)	(0.859)	(1.671)	(0.175)	(0.203)	(5.695)	(0.002)	(0.090)	(0.098)
Observations	832	832	832	240	832	832	832	240	832	832	832
R2	0.944	0.942	0.972	0.950	0.922	0.451	0.946	0.599	0.869	0.948	0.968
L3 GREENRATIOEP	0.401*	0.314*	0.076	−1.032	−3.344**	0.254	−0.253	−3.705	0.001	0.082	0.143
	(0.226)	(0.168)	(0.111)	(1.205)	(1.596)	(0.179)	(0.202)	(4.935)	(0.001)	(0.072)	(0.093)
Observations	698	698	698	114	698	698	698	114	698	698	698
R2	0.955	0.950	0.975	0.974	0.954	0.488	0.964	0.891	0.912	0.964	0.971
L5 GREENRATIOEP	0.426**	0.333**	0.155*		−1.334	0.371	0.070		0.001	0.024	0.135
	(0.194)	(0.152)	(0.091)		(2.018)	(0.256)	(0.225)		(0.001)	(0.079)	(0.091)
Observations	578	578	578		578	578	578		578	578	578
R2	0.965	0.961	0.979		0.969	0.567	0.975		0.924	0.971	0.975
L1 3YEARAVGGREENRATIOEP	0.739*	0.666**	0.043	1.671	−3.860	0.239	−0.314	−4.530	0.003	0.212	0.182
	(0.430)	(0.289)	(0.188)	(1.128)	(2.351)	(0.195)	(0.282)	(12.135)	(0.004)	(0.134)	(0.156)
Observations	869	869	869	250	869	869	869	250	869	869	869
R2	0.945	0.945	0.975	0.957	0.917	0.453	0.946	0.598	0.881	0.951	0.970
Panel A.3: And never-patenting firms											
L1 GREENRATIOEP	0.009	0.419**	0.026	0.953*	3.261*	0.370*	−0.199	2.588	0.003*	−0.024	0.112
	(0.169)	(0.169)	(0.116)	(0.528)	(1.734)	(0.206)	(0.318)	(2.608)	(0.002)	(0.088)	(0.109)
Observations	804	804	804	240	804	804	804	240	804	804	804
R2	0.938	0.917	0.942	0.969	0.935	0.437	0.355	0.977	0.822	0.928	0.945
L3 GREENRATIOEP	−0.303	0.000	−0.200*	0.180	−1.233	0.221	−0.591	−1.906	0.001	−0.173*	−0.078
	(0.189)	(0.159)	(0.115)	(0.439)	(1.026)	(0.136)	(0.367)	(1.958)	(0.002)	(0.094)	(0.096)
Observations	665	665	665	114	665	665	665	114	665	665	665
R2	0.948	0.931	0.958	0.997	0.977	0.645	0.693	0.997	0.871	0.941	0.956
L5 GREENRATIOEP	−0.369**	−0.140	−0.221*		−0.745	0.120	−0.523		0.002	−0.171*	−0.152
	(0.162)	(0.168)	(0.122)		(1.009)	(0.126)	(0.366)		(0.002)	(0.096)	(0.107)
Observations	543	543	543		543	543	543		543	543	543
R2	0.962	0.941	0.961		0.989	0.757	0.838		0.906	0.946	0.954
L1 3YEARAVGGREENRATIOEP	−0.014	0.521**	−0.001	1.500	1.536	0.696**	−0.381	7.747*	0.004	−0.134	0.122
	(0.232)	(0.257)	(0.160)	(1.100)	(1.832)	(0.304)	(0.302)	(4.450)	(0.002)	(0.125)	(0.144)
Observations	846	846	846	255	846	846	846	255	846	846	846
R2	0.938	0.908	0.939	0.973	0.932	0.445	0.359	0.977	0.812	0.919	0.939
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: ASIA-firm based GREENRATIOEP On Non-Asian firms											
Panel B.1: And all firms											
L1 GREENRATIOEP	0.058	0.091	0.008	1.040	−1.232	−0.018	−0.071	3.476	−0.000	−0.014	0.078
	(0.137)	(0.098)	(0.054)	(0.803)	(0.882)	(0.028)	(0.065)	(2.817)	(0.000)	(0.048)	(0.051)
Observations	834	834	834	240	834	834	834	240	834	834	834
R2	0.964	0.940	0.959	0.946	0.967	0.954	0.977	0.916	0.939	0.924	0.940
L3 GREENRATIOEP	−0.003	0.125*	0.023	0.143	−2.377***	−0.015	−0.172***	1.538	−0.001	−0.011	0.111**
	(0.133)	(0.075)	(0.048)	(0.451)	(0.829)	(0.022)	(0.056)	(2.017)	(0.000)	(0.037)	(0.045)
Observations	702	702	702	114	702	702	702	114	702	702	702
R2	0.980	0.975	0.982	0.990	0.979	0.975	0.985	0.994	0.950	0.978	0.981
L5 GREENRATIOEP	0.008	0.112*	−0.001		−0.916	−0.003	−0.100*		−0.001	−0.053	0.057
	(0.151)	(0.063)	(0.050)		(0.790)	(0.020)	(0.058)		(0.000)	(0.042)	(0.046)
Observations	584	584	584		584	584	584		584	584	584
R2	0.986	0.984	0.985		0.990	0.986	0.990		0.953	0.980	0.983
L1 3YEARAVGGREENRATIOEP	0.224	0.417**	0.094	−0.114	−3.299**	0.002	−0.237**	−1.320	−0.001	0.025	0.180**
	(0.166)	(0.170)	(0.078)	(1.315)	(1.454)	(0.042)	(0.104)	(6.565)	(0.001)	(0.063)	(0.084)
Observations	876	876	876	253	876	876	876	253	876	876	876
R2	0.965	0.944	0.961	0.953	0.968	0.954	0.976	0.916	0.943	0.927	0.944
Panel B.2: And ever-patenting firms											
L1 GREENRATIOEP	0.053	0.045	−0.001	1.054	−1.656*	−0.044	−0.085	0.901	0.000	0.071	0.071
	(0.152)	(0.117)	(0.066)	(1.085)	(0.971)	(0.033)	(0.072)	(5.648)	(0.000)	(0.045)	(0.063)
Observations	833	833	833	240	833	833	833	240	833	833	833
R2	0.958	0.950	0.971	0.938	0.935	0.942	0.972	0.863	0.950	0.970	0.968
L3 GREENRATIOEP	−0.107	0.024	−0.017	0.072	−2.643**	−0.036	−0.196***	1.135	−0.000	0.006	0.082
	(0.145)	(0.109)	(0.061)	(0.323)	(1.136)	(0.029)	(0.069)	(2.276)	(0.000)	(0.041)	(0.059)
Observations	701	701	701	114	701	701	701	114	701	701	701
R2	0.974	0.966	0.977	0.990	0.950	0.966	0.980	0.994	0.963	0.976	0.978
L5 GREENRATIOEP	−0.121	0.021	−0.011		−0.556	−0.022	−0.079		−0.000	−0.028	0.038
	(0.171)	(0.091)	(0.057)		(1.258)	(0.026)	(0.069)		(0.000)	(0.045)	(0.057)
Observations	583	583	583		583	583	583		583	583	583
R2	0.982	0.980	0.984		0.965	0.981	0.986		0.967	0.980	0.982
L1 3YEARAVGGREENRATIOEP	0.069	0.286	0.079	−0.294	−3.519**	−0.031	−0.252**	−12.296	−0.000	0.102	0.163
	(0.202)	(0.201)	(0.104)	(1.710)	(1.724)	(0.048)	(0.117)	(15.825)	(0.001)	(0.074)	(0.109)
Observations	875	875	875	253	875	875	875	253	875	875	875
R2	0.961	0.955	0.973	0.948	0.937	0.942	0.971	0.866	0.953	0.973	0.971
Panel B.3: And never-patenting firms											
L1 GREENRATIOEP	0.036	0.053	−0.031	0.086	0.187	0.017	−0.043	0.318	0.002	−0.265**	0.002
	(0.188)	(0.173)	(0.116)	(0.463)	(1.634)	(0.037)	(0.102)	(1.767)	(0.002)	(0.128)	(0.102)
Observations	790	790	790	240	790	790	790	240	790	789	790
R2	0.933	0.903	0.913	0.969	0.924	0.863	0.940	0.962	0.733	0.922	0.920
L3 GREENRATIOEP	0.201	0.044	0.013	0.358	−0.941	−0.005	−0.080	0.393	0.002	−0.122	0.038
	(0.159)	(0.121)	(0.098)	(0.304)	(1.241)	(0.049)	(0.074)	(0.725)	(0.002)	(0.080)	(0.082)
Observations	648	648	648	114	648	648	648	114	648	648	648
R2	0.957	0.941	0.943	0.998	0.953	0.929	0.961	0.998	0.758	0.953	0.946
L5 GREENRATIOEP	0.244*	0.091	0.007		−1.440	−0.007	−0.100		−0.001	−0.130	0.062
	(0.143)	(0.099)	(0.103)		(0.996)	(0.044)	(0.064)		(0.001)	(0.094)	(0.094)
Observations	524	524	524		524	524	524		524	524	524
R2	0.976	0.968	0.963		0.974	0.962	0.973		0.822	0.966	0.960
L1 3YEARAVGGREENRATIOEP	0.252	0.242	−0.138	−0.297	−1.461	0.143	−0.155	1.557	0.006*	−0.386***	−0.118
	(0.296)	(0.272)	(0.177)	(1.020)	(2.097)	(0.094)	(0.127)	(3.324)	(0.003)	(0.146)	(0.159)
Observations	829	829	829	253	829	829	829	253	829	828	829
R2	0.934	0.903	0.915	0.971	0.925	0.846	0.941	0.961	0.738	0.922	0.921
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXVIII. Brown Efficiency Patent Ratios in Asia and Cross-Country Industry-Level Outcomes

The unit of observation is GICS-6 industry-year. The sample period is 2005 to 2020. The dependent variables are GICS-6 sector industry level logs of cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A, dependent variables are calculated across all firms with their headquarter in Asia. In Panel B, dependent variables are calculated across all firms with their headquarter outside of Asia. In addition, in Panel A.1 and B.1, dependent variables are calculated across all firms within the given industry and region. In Panel A.2 and B.2, dependent variables are calculated across all ever patenting firms within the given industry and region and in Panel A.3 and B.3, dependent variables are calculated across all never patenting firms within the given industry and region. All independent variables are calculated based on firms with their headquarter in Asia. The key explanatory variables of interest is *BROWNEFFRATIOEP*. Controls include *LOGSIZE*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either GICS-6 industry level sums (LOGSIZE and LOGPPE), sum over sums (BROWNEFFRATIOEP, LEVERAGE, ROE, M/B, INVEST/A) or market capitalization value weighted averages (BETA, VOLAT, MOM, RET, MSCI). All Independent variables are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include year and industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: ASIA-firm based BROWNEFFRATIOEP On Asian firms											
Panel A.1: And all firms											
L1 BROWNEFFRATIOEP	−0.013	−0.545**	−0.095	1.048	5.499**	−0.296	0.580**	25.500	0.002	−0.106	−0.162
	(0.184)	(0.275)	(0.164)	(1.374)	(2.748)	(0.380)	(0.294)	(25.426)	(0.002)	(0.131)	(0.158)
Observations	835	835	835	240	835	835	835	240	835	835	835
R2	0.957	0.933	0.960	0.959	0.981	0.525	0.933	0.813	0.922	0.930	0.950
L3 BROWNEFFRATIOEP	0.070	−0.097	0.001	2.021	2.767	−0.585	0.306	23.884	0.002	−0.009	−0.012
	(0.188)	(0.203)	(0.111)	(2.231)	(2.035)	(0.439)	(0.323)	(29.066)	(0.002)	(0.090)	(0.108)
Observations	704	704	704	114	704	704	704	114	704	704	704
R2	0.973	0.956	0.981	0.987	0.994	0.568	0.967	0.962	0.940	0.965	0.976
L5 BROWNEFFRATIOEP	0.371*	−0.093	0.038		1.756	−0.638	0.082		0.001	0.065	0.025
	(0.190)	(0.208)	(0.096)		(1.647)	(0.418)	(0.317)		(0.002)	(0.088)	(0.120)
Observations	586	586	586		586	586	586		586	586	586
R2	0.978	0.964	0.983		0.997	0.648	0.978		0.949	0.965	0.975
L1 3YEARAVGBROWNEFFRATIOEP	0.212	−0.387	−0.052	4.553**	8.146*	−0.936	0.626*	52.914	0.000	−0.217	−0.085
	(0.238)	(0.306)	(0.191)	(2.237)	(4.257)	(0.674)	(0.342)	(42.805)	(0.002)	(0.201)	(0.194)
Observations	878	878	878	255	878	878	878	255	878	878	878
R2	0.957	0.935	0.960	0.967	0.978	0.531	0.933	0.818	0.907	0.920	0.950
Panel A.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	0.189	−0.753**	−0.070	−0.228	11.615***	−0.426	1.044**	37.607	0.006	−0.199	−0.241
	(0.420)	(0.353)	(0.214)	(1.972)	(4.230)	(0.494)	(0.454)	(39.020)	(0.004)	(0.167)	(0.174)
Observations	832	832	832	240	832	832	832	240	832	832	832
R2	0.944	0.943	0.972	0.949	0.929	0.452	0.947	0.609	0.869	0.948	0.968
L3 BROWNEFFRATIOEP	0.254	−0.451	−0.051	1.591	8.650*	−0.897	0.687	42.693	0.005	−0.092	−0.176
	(0.372)	(0.282)	(0.172)	(2.791)	(4.752)	(0.610)	(0.586)	(57.516)	(0.004)	(0.141)	(0.159)
Observations	698	698	698	114	698	698	698	114	698	698	698
R2	0.954	0.950	0.975	0.973	0.957	0.491	0.964	0.898	0.912	0.964	0.971
L5 BROWNEFFRATIOEP	0.548	−0.123	0.073		4.752	−0.810	0.409		0.006	0.055	−0.055
	(0.358)	(0.281)	(0.141)		(5.114)	(0.573)	(0.596)		(0.004)	(0.149)	(0.174)
Observations	578	578	578		578	578	578		578	578	578
R2	0.965	0.961	0.979		0.970	0.569	0.975		0.925	0.971	0.975
L1 3YEARAVGBROWNEFFRATIOEP	0.097	−1.069***	−0.044	3.407	18.429***	−1.235	1.306**	96.704	0.001	−0.354*	−0.235
	(0.487)	(0.381)	(0.231)	(2.690)	(5.820)	(0.876)	(0.542)	(84.731)	(0.004)	(0.191)	(0.171)
Observations	869	869	869	250	869	869	869	250	869	869	869
R2	0.945	0.945	0.975	0.957	0.926	0.456	0.948	0.626	0.881	0.951	0.970
Panel A.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	0.089	−0.329	0.151	0.608	6.483*	−0.232	1.069**	0.104	0.003	0.006	−0.019
	(0.190)	(0.283)	(0.167)	(0.987)	(3.442)	(0.450)	(0.515)	(5.464)	(0.002)	(0.142)	(0.155)
Observations	804	804	804	240	804	804	804	240	804	804	804
R2	0.938	0.917	0.942	0.968	0.935	0.435	0.356	0.977	0.822	0.928	0.945
L3 BROWNEFFRATIOEP	0.257	0.147	0.227	0.492	3.807*	−0.086	0.739	2.691	0.001	0.058	0.119
	(0.226)	(0.231)	(0.187)	(0.770)	(2.208)	(0.251)	(0.616)	(5.176)	(0.002)	(0.119)	(0.147)
Observations	665	665	665	114	665	665	665	114	665	665	665
R2	0.948	0.931	0.958	0.997	0.977	0.643	0.692	0.997	0.871	0.941	0.956
L5 BROWNEFFRATIOEP	0.215	−0.105	0.129		1.956	−0.482*	0.435		0.002	0.087	0.050
	(0.226)	(0.218)	(0.191)		(1.781)	(0.254)	(0.594)		(0.002)	(0.108)	(0.144)
Observations	543	543	543		543	543	543		543	543	543
R2	0.962	0.941	0.961		0.989	0.759	0.837		0.906	0.945	0.954
L1 3YEARAVGBROWNEFFRATIOEP	0.225	0.085	0.413*	3.375*	8.178	−0.458	0.491	9.997	0.003	−0.083	0.281
	(0.262)	(0.347)	(0.223)	(1.797)	(5.045)	(0.465)	(0.822)	(8.253)	(0.003)	(0.213)	(0.211)
Observations	846	846	846	255	846	846	846	255	846	846	846
R2	0.939	0.908	0.939	0.973	0.933	0.442	0.359	0.977	0.812	0.919	0.939
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: ASIA-firm based BROWNEFFRATIOEP On Non-Asian firms											
Panel B.1: And all firms											
L1 BROWNEFFRATIOEP	0.126	−0.159	−0.006	−0.760	4.276	−0.158*	0.185	−8.662*	0.001	0.001	−0.144
	(0.104)	(0.187)	(0.077)	(1.341)	(2.658)	(0.093)	(0.145)	(5.228)	(0.001)	(0.081)	(0.094)
Observations	834	834	834	240	834	834	834	240	834	834	834
R2	0.964	0.940	0.959	0.945	0.968	0.954	0.977	0.916	0.939	0.924	0.940
L3 BROWNEFFRATIOEP	−0.079	−0.146	−0.085	1.430	4.972**	−0.107	0.208**	6.432	0.001	−0.061	−0.172**
	(0.103)	(0.121)	(0.070)	(1.913)	(2.170)	(0.075)	(0.098)	(9.528)	(0.001)	(0.074)	(0.081)
Observations	702	702	702	114	702	702	702	114	702	702	702
R2	0.980	0.975	0.982	0.990	0.980	0.975	0.985	0.994	0.950	0.978	0.981
L5 BROWNEFFRATIOEP	−0.065	−0.098	−0.009		1.661	−0.088	0.144		0.000	−0.028	−0.050
	(0.083)	(0.081)	(0.081)		(2.017)	(0.054)	(0.094)		(0.001)	(0.079)	(0.098)
Observations	584	584	584		584	584	584		584	584	584
R2	0.986	0.984	0.985		0.990	0.986	0.990		0.953	0.980	0.983
L1 3YEARAVGBROWNEFFRATIOEP	0.250	−0.188	0.194	3.476**	8.198**	−0.318**	0.410*	9.146	0.001	−0.064	−0.099
	(0.188)	(0.238)	(0.146)	(1.710)	(3.475)	(0.148)	(0.211)	(7.366)	(0.001)	(0.124)	(0.165)
Observations	876	876	876	253	876	876	876	253	876	876	876
R2	0.965	0.944	0.961	0.954	0.971	0.955	0.976	0.917	0.942	0.927	0.944
Panel B.2: And ever-patenting firms											
L1 BROWNEFFRATIOEP	0.130	−0.288	−0.093	−0.882	5.801**	−0.152	0.230	−5.320	0.000	−0.015	−0.238*
	(0.112)	(0.289)	(0.101)	(1.374)	(2.665)	(0.099)	(0.162)	(6.453)	(0.001)	(0.075)	(0.122)
Observations	833	833	833	240	833	833	833	240	833	833	833
R2	0.958	0.950	0.971	0.937	0.939	0.942	0.972	0.863	0.950	0.970	0.968
L3 BROWNEFFRATIOEP	0.010	−0.178	−0.108	−0.878	6.216**	−0.098	0.298**	−2.894	0.000	−0.023	−0.227*
	(0.101)	(0.162)	(0.092)	(1.372)	(3.003)	(0.082)	(0.128)	(10.363)	(0.000)	(0.072)	(0.116)
Observations	701	701	701	114	701	701	701	114	701	701	701
R2	0.974	0.966	0.977	0.990	0.953	0.966	0.980	0.994	0.963	0.976	0.978
L5 BROWNEFFRATIOEP	0.008	−0.063	0.033		1.374	−0.093	0.164		−0.000	0.033	−0.014
	(0.087)	(0.117)	(0.090)		(3.582)	(0.061)	(0.131)		(0.000)	(0.061)	(0.125)
Observations	583	583	583		583	583	583		583	583	583
R2	0.982	0.980	0.984		0.965	0.981	0.986		0.967	0.980	0.982
L1 3YEARAVGBROWNEFFRATIOEP	0.321*	−0.063	0.140	4.766**	8.468**	−0.298*	0.414*	24.659	0.001	0.198*	−0.109
	(0.184)	(0.286)	(0.194)	(2.345)	(4.007)	(0.153)	(0.230)	(17.383)	(0.001)	(0.119)	(0.214)
Observations	875	875	875	253	875	875	875	253	875	875	875
R2	0.961	0.954	0.973	0.950	0.941	0.944	0.971	0.867	0.953	0.973	0.971
Panel B.3: And never-patenting firms											
L1 BROWNEFFRATIOEP	0.191	0.108	−0.046	1.398	1.913	−0.049	−0.361*	2.880	0.000	0.104	0.066
	(0.178)	(0.276)	(0.137)	(0.871)	(6.497)	(0.069)	(0.200)	(4.012)	(0.002)	(0.176)	(0.122)
Observations	790	790	790	240	790	790	790	240	790	789	790
R2	0.933	0.903	0.913	0.970	0.924	0.863	0.941	0.962	0.733	0.921	0.920
L3 BROWNEFFRATIOEP	−0.211	−0.011	−0.275**	0.036	1.077	−0.040	−0.378**	−0.037	0.002	−0.085	−0.090
	(0.149)	(0.199)	(0.125)	(1.207)	(4.322)	(0.048)	(0.180)	(3.477)	(0.002)	(0.126)	(0.094)
Observations	648	648	648	114	648	648	648	114	648	648	648
R2	0.957	0.941	0.943	0.998	0.953	0.929	0.961	0.998	0.758	0.953	0.946
L5 BROWNEFFRATIOEP	−0.092	0.020	−0.154		2.047	−0.030	−0.155		0.002	−0.047	−0.063
	(0.115)	(0.133)	(0.115)		(2.741)	(0.034)	(0.140)		(0.002)	(0.113)	(0.091)
Observations	524	524	524		524	524	524		524	524	524
R2	0.976	0.968	0.963		0.974	0.962	0.973		0.822	0.966	0.960
L1 3YEARAVGBROWNEFFRATIOEP	0.251	−0.342	−0.181	1.493	7.455	−0.166	−0.536*	−0.612	−0.000	−0.120	0.079
	(0.298)	(0.372)	(0.235)	(1.284)	(6.683)	(0.110)	(0.294)	(4.285)	(0.004)	(0.242)	(0.217)
Observations	829	829	829	253	829	829	829	253	829	828	829
R2	0.934	0.903	0.915	0.971	0.927	0.845	0.941	0.961	0.738	0.922	0.921
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table B.XXIX. Ex-post characteristics of indirect emission decreasing vs increasing firms

The unit of observation is firm-year and the sample period is 2005 to 2020. To split firms in emission reduction samples (column 1 to 4) and emission increase samples (column 5 to 8) we calculate changes in emissions over three years. Panel A covers total scope 2 emissions, Panel B upstream scope 3 emissions and Panel C downstream scope 3 emissions. We calculate mean, standard deviation, median and the count for each sample as well as the difference and p-value between the two samples for a variety of variables at the three year lag. Panel A.1, B.1 and C.1 cover the full Trucost sample. Panel A.2, B.2 and C.2 zoom in on the Trucost sample with at least one patent at the European Patent Office and the greatest emission change. Within the emission decrease sample, we focus on the 50% with the greatest emission decrease. Similarly within the emission increase sample, we focus on the 50% with the greatest emission increase. DUMMYANYEP (DUMMYGREENEP, DUMMYBROWNEFFEP, and DUMMYOECDEP) are dummies equal to one if a firm has at least one (one green, one brown efficiency and one OECD env-tech) patent and zero otherwise. SALES3YRCHG is the change in sales across the three year period in decimals. All other variables are defined in Table 3.1, Table 3.2 and Table 3.4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Emission decrease sample				Emission increase sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: 3-year changes in scope 2 emissions										
Panel A.1: Patenting and non-patenting firms										
DUMMYANYEP	0.296	0.457	0.000	29199	0.292	0.455	0.000	42027	0.004	0.228
DUMMYGREENEP	0.138	0.345	0.000	29199	0.126	0.332	0.000	42027	0.012	0.000
DUMMYBROWNEFFEP	0.065	0.247	0.000	29199	0.057	0.232	0.000	42027	0.008	0.000
DUMMYOECDEP	0.144	0.351	0.000	29199	0.129	0.335	0.000	42027	0.015	0.000
AGE	47.280	38.773	34.000	27271	41.438	35.990	28.000	39054	5.842	0.000
LOGSIZE	7.690	1.701	7.723	29199	7.714	1.548	7.762	42027	−0.023	0.062
LOGPPE	5.962	2.376	6.162	29199	5.871	2.278	6.051	42027	0.092	0.000
MB	2.402	2.706	1.606	29199	2.774	2.927	1.859	42027	−0.373	0.000
LEVERAGE	24.072	18.132	22.416	29199	23.187	18.131	21.237	42027	0.885	0.000
ROE	10.519	27.006	10.359	29199	11.960	23.463	11.477	42027	−1.441	0.000
SALES3YRCHG	−0.117	0.537	−0.038	29138	0.314	0.501	0.241	41957	−0.431	0.000
Panel A.2: Firm-years with at least one EP patent & greatest emission decreases, resp. increases										
GREENRATIOEP	12.646	24.618	0.000	4325	12.119	24.608	0.000	6136	0.527	0.281
BROWNEFFRATIOEP	4.305	14.269	0.000	4325	3.406	13.053	0.000	6136	0.898	0.001
OECDRATIOEP	13.876	25.314	0.000	4325	12.233	24.368	0.000	6136	1.643	0.001
GREENCITMAXEP	44.640	187.160	0.000	4325	65.211	573.680	0.000	6136	−20.571	0.009
BROWNEFFCITMAXEP	13.322	223.038	0.000	4325	9.421	47.241	0.000	6136	3.901	0.257
GREENCOUNTBBEP	0.230	1.042	0.000	4325	0.212	1.018	0.000	6136	0.018	0.373
BROWNEFFCOUNTBBEP	0.093	0.794	0.000	4325	0.063	0.431	0.000	6136	0.030	0.024
AGE	56.880	42.765	45.000	4281	47.383	39.415	33.000	6094	9.496	0.000
LOGSIZE	8.353	1.688	8.361	4325	8.291	1.575	8.271	6136	0.062	0.058
LOGPPE	6.747	2.209	6.847	4325	6.446	2.143	6.508	6136	0.300	0.000
MB	2.551	2.717	1.778	4325	3.174	3.171	2.211	6136	−0.623	0.000
LEVERAGE	23.615	15.744	22.637	4325	22.291	16.697	21.329	6136	1.325	0.000
ROE	8.585	29.419	10.271	4325	9.604	28.328	11.476	6136	−1.019	0.076
SALES3YRCHG	−0.163	0.579	−0.075	4321	0.401	0.587	0.324	6132	−0.564	0.000
Panel B: 3-year changes in upstream scope 3 emissions										
Panel B.1: Patenting and non-patenting firms										
DUMMYANYEP	0.298	0.458	0.000	28408	0.290	0.454	0.000	42885	0.008	0.026
DUMMYGREENEP	0.140	0.347	0.000	28408	0.125	0.330	0.000	42885	0.015	0.000
DUMMYBROWNEFFEP	0.069	0.253	0.000	28408	0.055	0.228	0.000	42885	0.013	0.000
DUMMYOECDEP	0.146	0.353	0.000	28408	0.128	0.334	0.000	42885	0.018	0.000
AGE	46.931	38.457	34.000	26627	41.749	36.293	29.000	39765	5.182	0.000
LOGSIZE	7.631	1.672	7.690	28408	7.754	1.569	7.785	42885	−0.124	0.000
LOGPPE	6.062	2.356	6.255	28408	5.808	2.290	6.000	42885	0.254	0.000
MB	2.248	2.547	1.528	28408	2.869	3.000	1.931	42885	−0.621	0.000
LEVERAGE	24.414	18.091	22.840	28408	22.983	18.146	20.968	42885	1.430	0.000
ROE	9.732	26.444	9.981	28408	12.452	23.891	11.721	42885	−2.720	0.000
SALES3YRCHG	−0.198	0.507	−0.102	28347	0.360	0.473	0.266	42815	−0.558	0.000
Panel B.2: Firm-years with at least one EP patent & greatest emission decreases, resp. increases										
GREENRATIOEP	13.261	25.164	0.000	4237	11.883	24.392	0.000	6229	1.377	0.005
BROWNEFFRATIOEP	4.592	14.783	0.000	4237	3.370	13.040	0.000	6229	1.222	0.000
OECDRATIOEP	14.522	26.082	0.000	4237	11.960	24.008	0.000	6229	2.561	0.000
GREENCITMAXEP	47.269	187.291	0.000	4237	54.588	327.325	0.000	6229	−7.320	0.147
BROWNEFFCITMAXEP	19.165	317.144	0.000	4237	8.678	42.631	0.000	6229	10.487	0.032
GREENCOUNTBBEP	0.243	1.098	0.000	4237	0.216	0.925	0.000	6229	0.026	0.198
BROWNEFFCOUNTBBEP	0.123	0.928	0.000	4237	0.067	0.496	0.000	6229	0.056	0.000
AGE	57.208	43.746	46.000	4215	45.397	39.138	31.000	6168	11.812	0.000
LOGSIZE	8.234	1.696	8.227	4237	8.294	1.611	8.285	6229	−0.060	0.070
LOGPPE	6.889	2.256	7.039	4237	6.222	2.139	6.266	6229	0.667	0.000
MB	2.215	2.428	1.601	4237	3.526	3.384	2.512	6229	−1.310	0.000
LEVERAGE	24.170	16.037	23.076	4237	21.742	16.918	20.308	6229	2.428	0.000
ROE	7.362	29.766	9.306	4237	10.395	29.696	11.984	6229	−3.033	0.000
SALES3YRCHG	−0.315	0.528	−0.217	4232	0.497	0.533	0.392	6226	−0.812	0.000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Emission decrease sample				Emission increase sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel C: 3-year changes in downstream scope 3 emissions										
Panel C.1: Patenting and non-patenting firms										
DUMMYANYEP	0.244	0.430	0.000	6412	0.210	0.407	0.000	4628	0.034	0.000
DUMMYGREENEP	0.094	0.292	0.000	6412	0.082	0.275	0.000	4628	0.012	0.026
DUMMYBROWNEFFEP	0.041	0.198	0.000	6412	0.033	0.179	0.000	4628	0.008	0.036
DUMMYOECDEP	0.094	0.292	0.000	6412	0.079	0.270	0.000	4628	0.015	0.005
AGE	42.999	33.724	32.000	5865	37.566	32.005	26.000	4219	5.433	0.000
LOGSIZE	7.128	1.550	7.053	6412	7.218	1.631	7.115	4628	−0.090	0.003
LOGPPE	5.214	2.232	5.306	6412	4.933	2.374	5.030	4628	0.282	0.000
MB	2.609	2.827	1.735	6412	2.971	3.225	1.879	4628	−0.362	0.000
LEVERAGE	22.372	18.573	19.725	6412	22.749	18.804	20.577	4628	−0.377	0.296
ROE	9.932	22.883	9.682	6412	9.211	25.840	9.994	4628	0.721	0.130
SALES3YRCHG	−0.012	0.526	0.061	6408	0.268	0.603	0.184	4624	−0.280	0.000
Panel C.2: Firm-years with at least one EP patent & greatest emission decreases, resp. increases										
GREENRATIOEP	11.955	23.128	0.000	784	13.742	26.184	0.000	486	−1.787	0.217
BROWNEFFRATIOEP	2.861	11.181	0.000	784	2.346	9.927	0.000	486	0.516	0.392
OECDRATIOEP	12.019	23.823	0.000	784	9.269	21.192	0.000	486	2.750	0.032
GREENCITMAXEP	16.356	103.591	0.000	784	72.142	1115.594	0.000	486	−55.786	0.272
BROWNEFFCITMAXEP	3.171	14.083	0.000	784	2.891	13.033	0.000	486	0.280	0.718
GREENCOUNTBBEP	0.255	1.489	0.000	784	0.226	0.853	0.000	486	0.029	0.662
BROWNEFFCOUNTBBEP	0.101	1.160	0.000	784	0.109	1.062	0.000	486	−0.008	0.896
AGE	54.055	39.770	45.000	781	46.300	39.119	31.000	477	7.755	0.001
LOGSIZE	7.760	1.680	7.706	784	8.113	1.850	8.094	486	−0.354	0.001
LOGPPE	5.916	2.111	5.913	784	5.629	2.519	5.744	486	0.287	0.036
MB	2.916	2.942	2.071	784	3.981	3.858	2.817	486	−1.065	0.000
LEVERAGE	21.707	16.440	21.170	784	21.921	18.852	19.407	486	−0.214	0.837
ROE	8.980	26.828	9.502	784	5.596	38.696	10.700	486	3.384	0.091
SALES3YRCHG	−0.038	0.552	0.045	784	0.440	0.830	0.203	486	−0.478	0.000

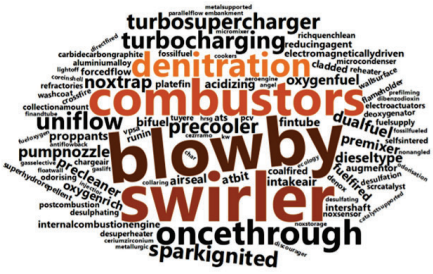
B.2 Appendix Figures

Figure B.I. Patents from specific patent classifications vs all other patents

The sample is all patents granted by the European Patent Office from 2005 to 2020 that belong to the Trucost sample. The wordclouds display the top 100 words (unigrams) based on the TF-IDF comparing patent titles of patents in the given classification to all other patents. We compare "green" patent titles to all other patent titles in Panel A, "brown efficiency" to all others in Panel B, "general efficiency" to all others in Panel C, OECD-env tech to all others in Panel D, IPC green inventory to all others in Panel E, Corporate Knights self classified to all others in Panel F, and Fossil Fuel technologies to all others in Panel G.

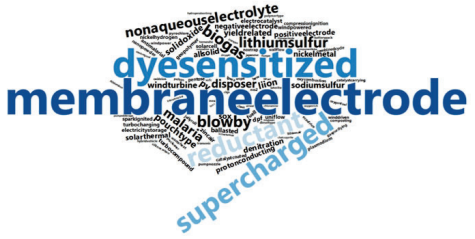
(a) Green against all others

(b) Brown efficiency against all others



(c) General efficiency against all others

(d) OECD against all others



(e) IPC against all others

(f) CK against all others

(g) FF against all others

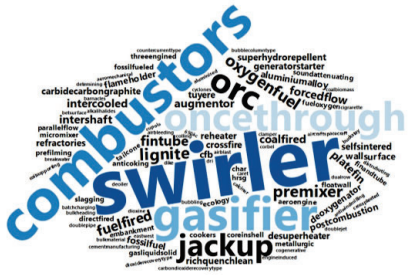


Figure B.II. Patent Ratios For Halliburton Company

We report GREENRATIOEP, BROWNEFFRATIOEP and OECDRATIOEP for Halliburton Company per year between 2005 and 2020. The variables are defined in Table 3.2 and Table B.V.

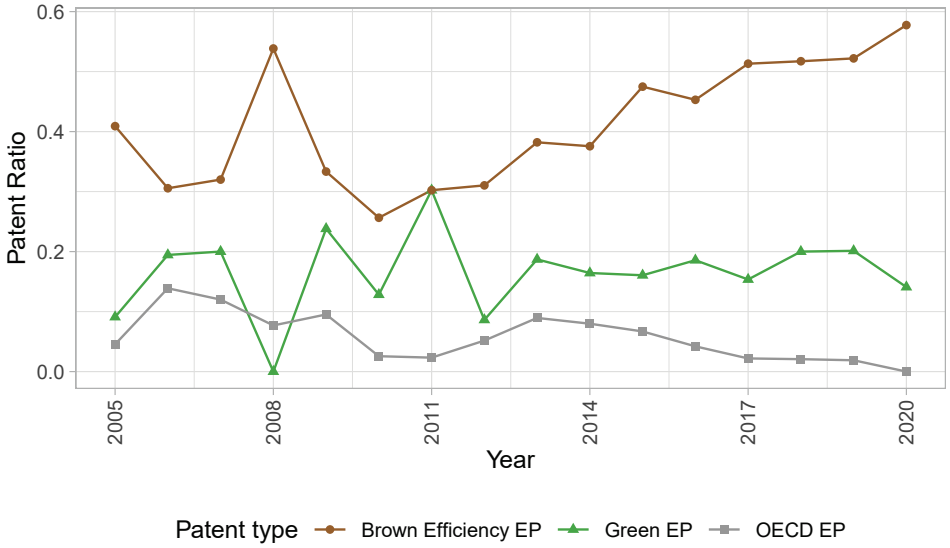
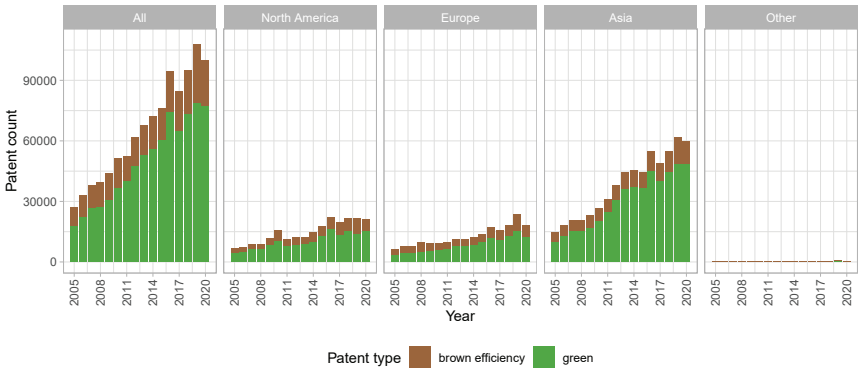


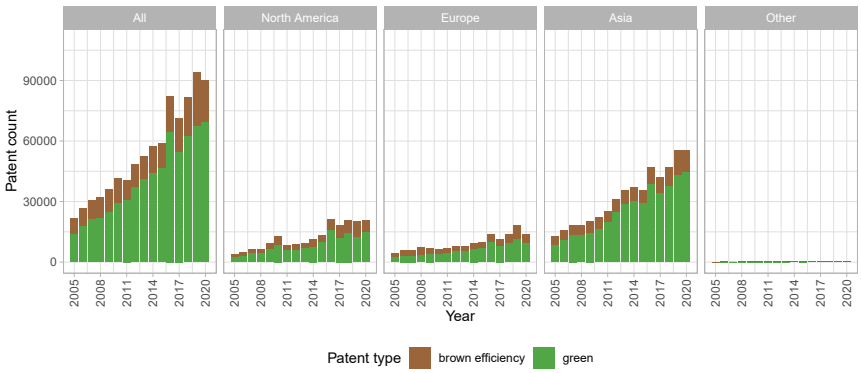
Figure B.III. Green and Brown Efficiency Worldwide Patent Counts Across Regions

The sample period is 2005 to 2020. We report the total number of granted or purchased green and brown efficiency patent families from world wide patent offices. We report the total across all regions and by region, namely North America, Europe, Asia, and other (rest of the world), per year. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.

(a) Full (public/private) sample



(b) Trucost sample



(c) Trucost (pre 2016) legacy sample

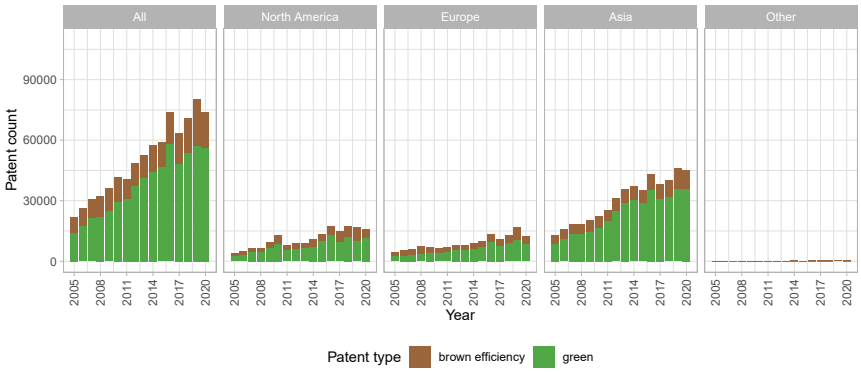
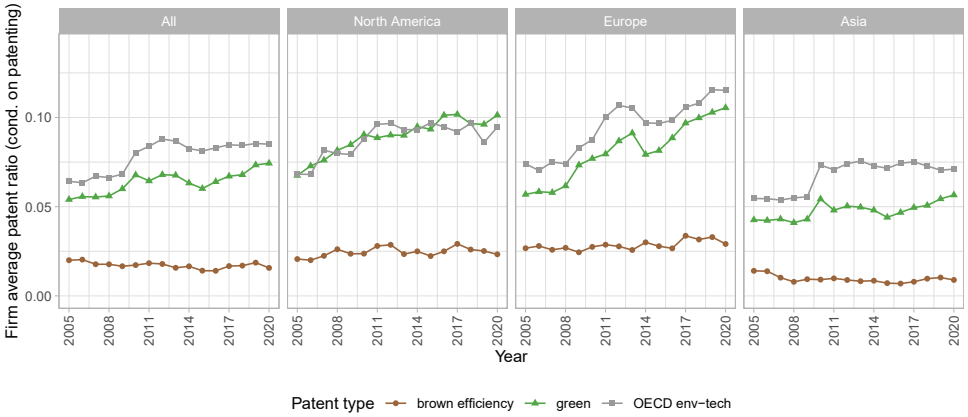


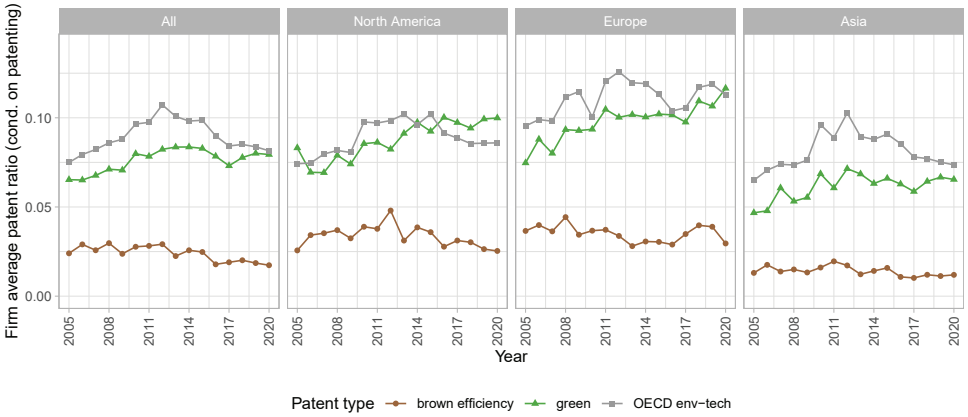
Figure B.IV. Green and Brown Efficiency Worldwide Patent Ratios Across Regions

The sample period is 2005 to 2020. We report the average GREENRATIOWW, BROWNEFFRATIOWW and OECDRATIOWW across all regions and for the regions North America, Europe and Asia per year. The patent ratios are defined in Table B.IX and capture worldwide patent office activity. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.

(a) Full (public/private) sample



(b) Trucost sample



(c) Trucost (pre 2016) legacy sample

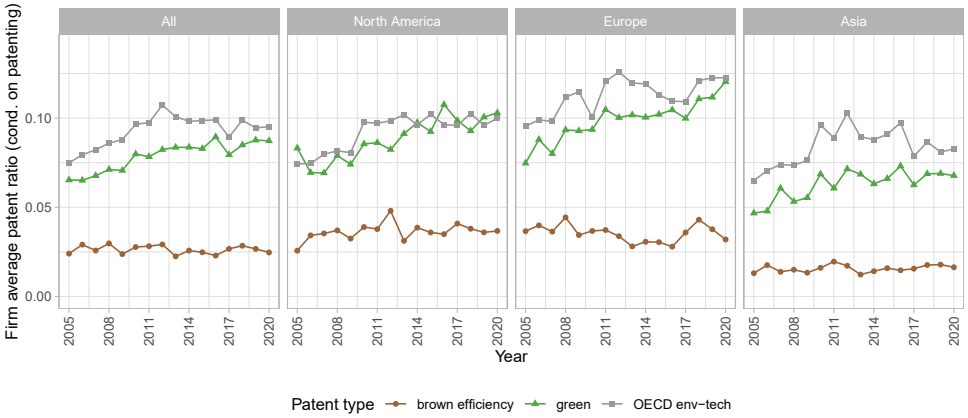
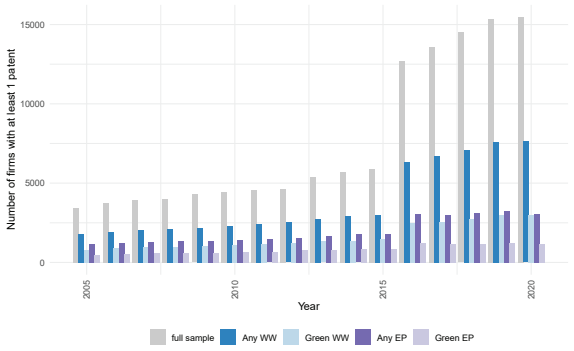


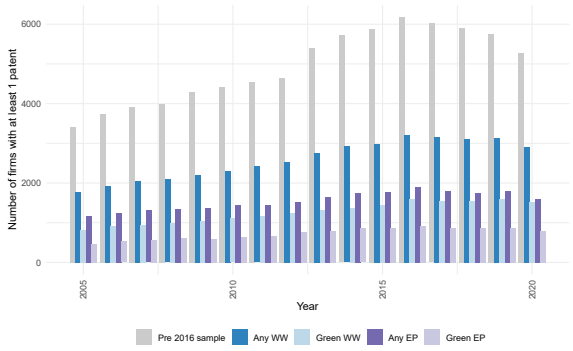
Figure B.V. Firm-year observations with at least one granted/purchased patent per year

Each graph presents the annual number of firms from the whole Trucost sample (full sample - grey bars), that have a patent granted or purchased at any patent office world wide (Any WW - dark blue bars), that have a green patent granted or purchased at any patent office world wide (Green WW - light blue bars), that have a patent granted or purchased at the European Patent Office wide (Any EP - dark purple bars), that have a green patent granted or purchased at the European Patent Office (Green EP - light purple bars). Panel A covers the full sample. Panel B is restricted to firms with emission data from Trucost prior to 2016. Panel C is restricted to firms with emission data from Trucost in 2006.

(a) Full Sample



(b) Pre 2016 Legacy Sample



(c) Pre 2006 Legacy Sample

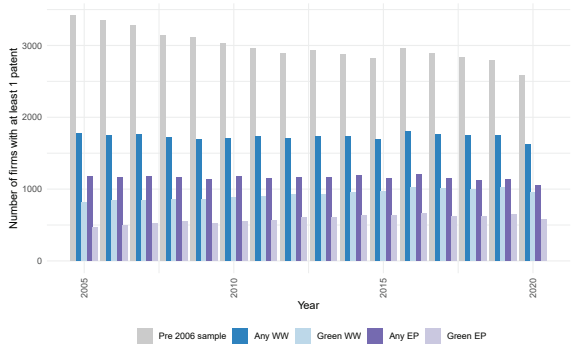
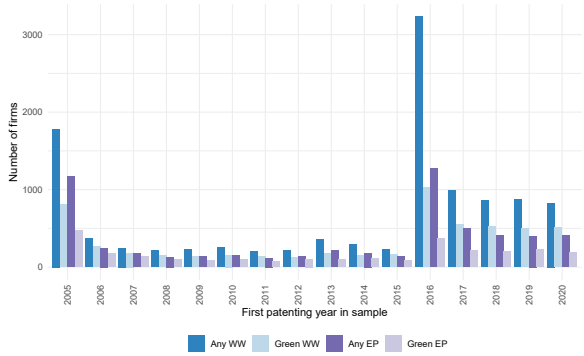


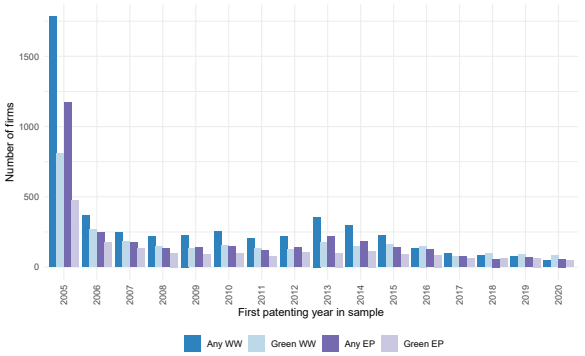
Figure B.VI. Firm count by first year with a granted/purchased patent

Each graph covers the Trucost sample and documents a firm's first year with a granted or purchased patent. The bars represent the number of firms with their first patent in the given year. Dark blue bars cover any patent from any patent office world wide (Any WW), light blue bars cover green patents from any patent office world wide (Green WW), dark purple bars cover any patent from the European Patent Office (Any EP) and light purple bars cover green patents from the European Patent Office (Green EP). Panel A covers the full sample. Panel B is restricted to firms with emission data from Trucost prior to 2016. Panel C is restricted to firms with emission data from Trucost in 2006.

(a) Full Sample



(b) Pre 2016 Legacy Sample



(c) Pre 2006 Legacy Sample

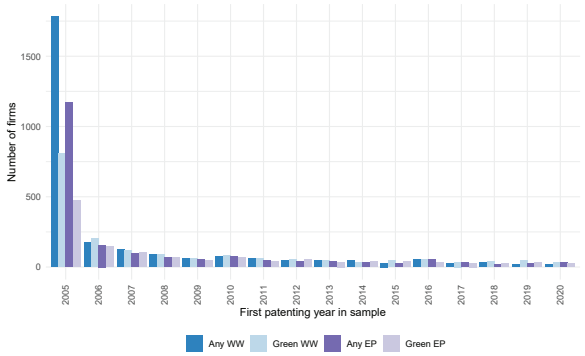
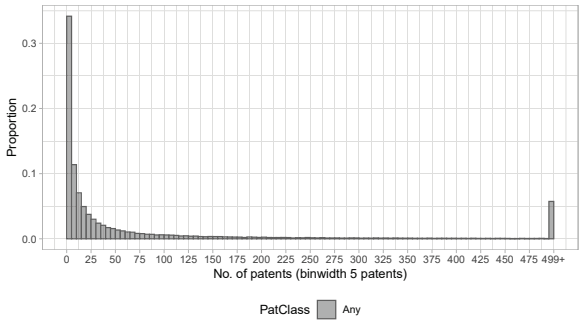


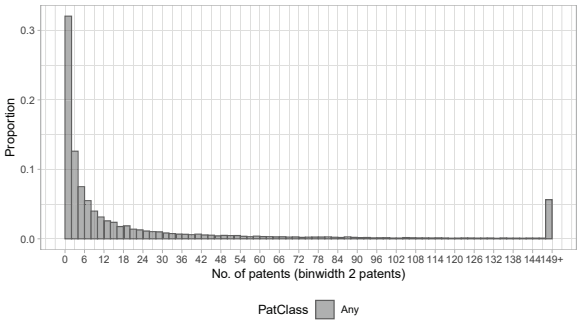
Figure B.VII. Histograms of patent counts for firm-year observations

The histograms plot the proportion of firm-year observations in bins based on the number of granted/purchased patents for the Trucost sample between 2005 and 2020. In Panel A, the patent count is based on patents granted or purchased at any patent office worldwide accounting for patent families. The binwidth is 5 patents. The last bin is an overflow bin with 499 patents and more. In Panel B, the patent count is based on patents granted or purchased by the European Patent Office and the binwidth is 2 patents. The last bin is an overflow bin with 149 patents and more.

(a) Worldwide patent office



(b) European patent office



Appendix C

Opioid Crisis and Real Estate Prices

C.1 Opioid laws and regulations

Figure C.I. Passage of opioids legislation by state

We colour states by the year in which they passed an opioid distribution law or regulation.

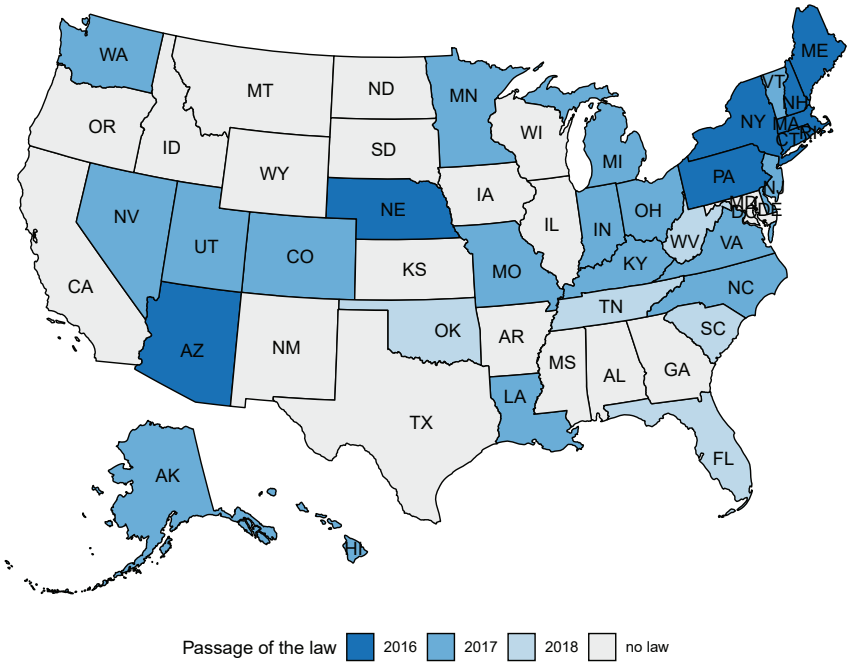


Table C.I. Determinants of opioids state legislation

This is a cross-sectional regression with all 50 US states. The dependent variable is an indicator variable equal to one if a state passed a opioid law or regulation between 2016 and 2018. Following Ouimet, Simintzi, and Ye (2021), independent variables include: Average state prescription rate between 2006 and 2015 per 100,000 people; Age adjusted overdose death rate, unemployment rate, ln(median household income in current dollars), poverty ratio, ln(GDP per capita in current dollars) at the state level as of 2015; Democratic and Republican are indicators that equal one if the state governor, state senate and state house are all Democratic, respectively all Republican, in 2015. Standard errors are robust. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)
	State Law and Regulation Indicator			
Avg Prescription Rate	−0.003	0.004	−0.002	0.004
	(0.003)	(0.006)	(0.004)	(0.006)
Age Adjusted Overdose Death Rate	0.031***	0.027**	0.029**	0.026**
	(0.011)	(0.012)	(0.012)	(0.013)
Unemployment Rate		−0.008		−0.010
		(0.085)		(0.089)
Ln(Median Household Income)		1.505		1.527
		(1.241)		(1.290)
Poverty Ratio		0.041		0.042
		(0.051)		(0.052)
Ln(GDP per capita)		0.132		0.112
		(0.610)		(0.634)
Democratic			0.003	0.030
			(0.203)	(0.211)
Republican			−0.071	−0.015
			(0.165)	(0.176)
R2	0.159	0.208	0.163	0.209
N	50	50	50	50

Table C.II. County/State observations for opioid law introductions

The table reports the number of states that passed laws intended limit opioid abuse as well as the number of observations with data for opioid prescriptions, respectivelyu home value, at the county level.

	Opioid Prescriptions Observations		Home Value Observations	
	States	Counties	States	Counties
State Law Passed in 2016	9	279	9	253
State Law Passed in 2017	18	1095	18	1060
State Law Passed in 2018	5	340	5	334

Figure C.II. The effect of opioid limiting laws on overdose death

The sample period is 2013 to 2018. The dependent variable is the annual overdose death rate in Panel A and the percentage change in the annual overdose death rate in % in Panel B. We restrict the sample to counties with overdose death data in every period between 2013 and 2018. Controls include one year-lagged male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We plot the interaction weighted total coefficient with a 95% confidence interval for each relative time period following Sun and Abraham (2021a). Standard errors are clustered at the state level.

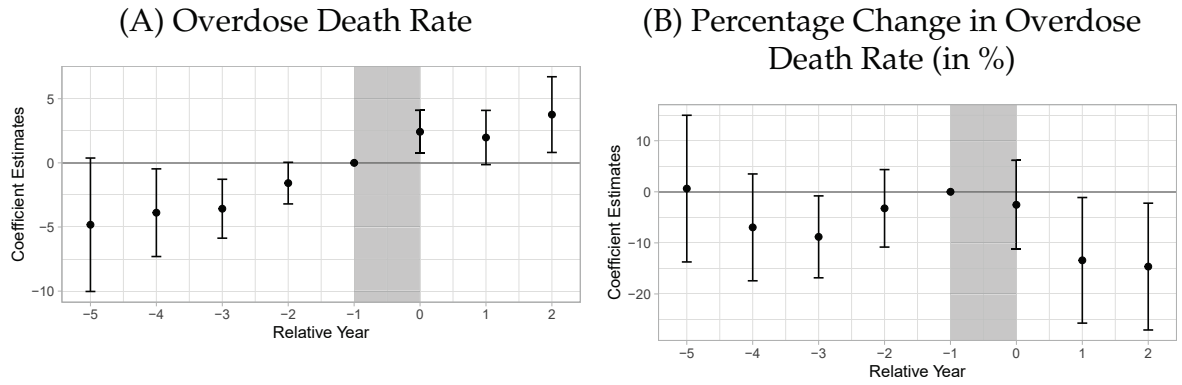


Figure C.III. Event plot for home value with hypothesized trend based on 50% power

The sample period is 2013 to 2018. The dependent variable is log percentage change in average county home values. We follow Roth (2022) and plot a linear violation of the pre trend based on a 50% power in red. Black are coefficients we find in our regression and blue are the expected coefficient we would find based on the hypothesized trend in red.

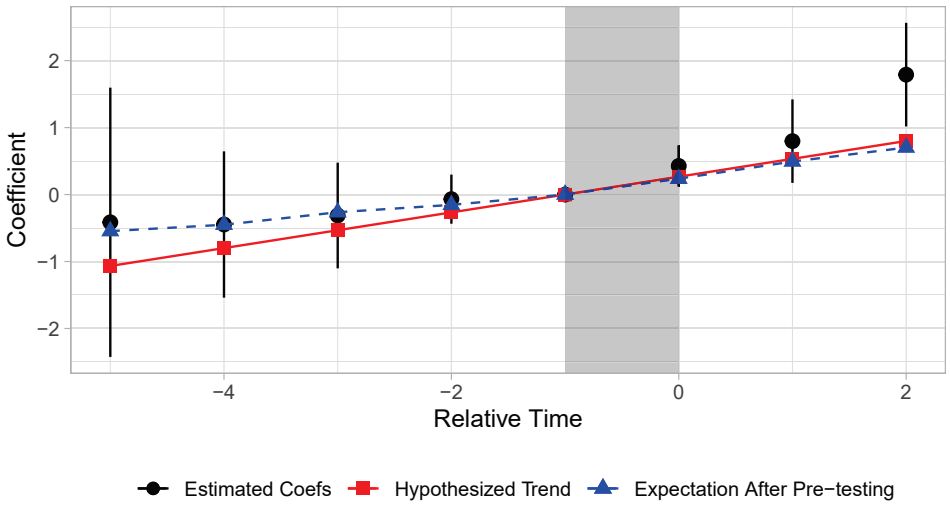


Figure C.IV. The effect of opioid limiting laws on rent

The sample period is 2013 to 2018. The dependent variable is log percentage change in median rent. Controls include one year-lagged male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. We plot the interaction weighted total coefficient with a 95% confidence interval for each relative time period following Sun and Abraham (2021a). Standard errors are clustered at the state level.

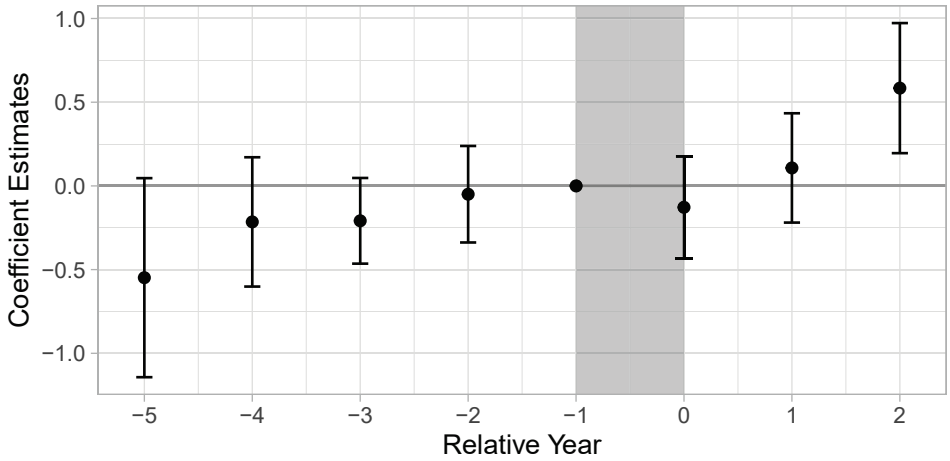
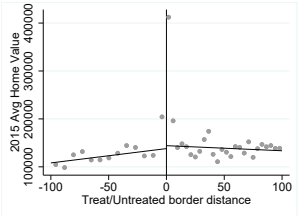
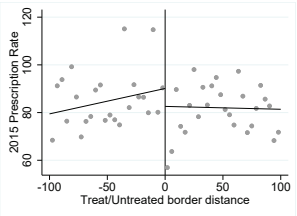


Figure C.V. Regression discontinuity plots for covariates in 2015

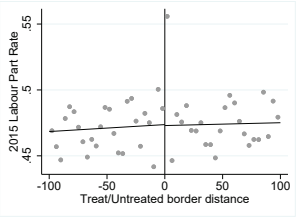
The unit of observations are counties. The dependent variables are levels in home value (Panel A), prescription rate (Panel B), labour participation rate (Panel C), unemployment rate (Panel D) and poverty ratio (Panel E) as of 2015. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth and do not include any other controls. Standard errors are clustered at the state level.



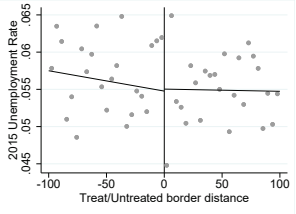
(a) Home Value



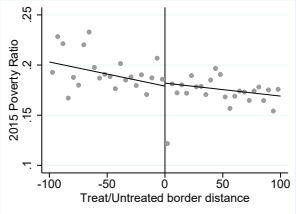
(b) Prescription Rate



(c) Labour participation rate



(d) Unemployment Rate



(e) Poverty Ratio

C.2 Economic mechanisms

Table C.III. Summary statistics economic mechanisms

We report summary statistic for the economic mechanism variables delinquent mortgages, home improvement loans and residential vacancy rates in Panel A and for migration outflow and inflow in Panel B.

Panel A: Summary statistics: Channel variables									
	N total	Avg N Annual	Mean	Min	P25	Median	P75	Max	Std. Dev.
Percent of Mortgages 90+ days past due	5,170	470	2.41	0.42	1.27	2.06	3.16	7.36	1.55
5- year Perc Change Mtgs 90+ days past (in %)	2,820	470	-66.98	-195.90	-113.08	-75.51	-29.35	94.28	68.83
No. of home purchase loans	38,290	3,191	894.51	5.00	62.00	190.00	644.00	9,480.96	1,865.67
5-year Perc Change home pruchase loans (in %)	22,208	3,173	16.82	-88.31	-9.65	23.19	48.10	98.90	43.96
Residential vacancy rate (in %)	28,109	3,123	4.25	0.00	1.56	3.41	5.98	15.27	3.64
5-year Perc Change residential vacancy rate (in %)	11,335	2,834	-14.01	-833.29	-33.51	-7.03	14.31	639.88	79.47
Panel B: Summary statistics: Migration									
	N total	Avg N Annual	Mean	Min	P25	Median	P75	Max	Std. Dev.
Log(Mig-out total income)	40,586	3,122	10.18	7.29	9.08	9.97	11.13	14.08	1.57
5-year Perc Change Mig-out total income (in %)	24,923	3,115	12.97	-49.82	-2.57	13.05	28.88	69.77	25.24
Log(Mig-out no households)	40,607	3,124	6.54	3.69	5.56	6.40	7.42	9.99	1.44
5-year Perc Change Mig-out no households (in %)	24,949	3,119	-1.91	-49.79	-12.54	-1.07	9.60	36.78	18.22
Log(Mig-out no individuals)	40,607	3,124	7.20	4.33	6.24	7.07	8.06	10.59	1.42
5-year Perc Change Mig-outno individuals (in %)	24,949	3,119	-0.93	-51.03	-12.73	0.07	11.90	40.07	19.52
Log(Mig-in total income)	40,535	3,118	10.18	7.18	9.03	10.00	11.19	14.04	1.61
Log(Mig-in no households)	40,556	3,120	6.51	3.61	5.51	6.37	7.43	9.99	1.47
Log(Mig-in no individuals)	40,556	3,120	7.21	4.32	6.23	7.07	8.09	10.58	1.44

C.3 Internet Appendix

C.3.1 Opioid laws and regulations

Opioid Laws and Regulations Passed between 2016 and 2018

Alaska (*2017 / Law*) limits first-time opioid prescriptions to seven days except for chronic pain or patients with travel/ logistical barriers.

Arizona (*2016 / Regulation*) limits first-time opioid prescriptions to seven days for insured people under state's Medicaid or state's employee insurance plan. In 2018, a new law limits first-time opioid prescription to five days.

Colorado (*2017 / Regulation*) limits first-time opioid prescriptions to seven days with 2 more seven-day prescriptions and a fourth seven-day prescriptions upon department approval possible. In 2018, a new law limits first-time opioid prescription to seven days with one possible seven day extensions. Exceptions include chronic pain patients, cancer patients, patients under hospice care, and patients experiencing post-surgical pain.

Connecticut (*2016 / Law*) limits first-time opioid prescriptions to seven days except for chronic pain patients. in 2018, a second law reduce opioid prescription limits for minors from seven days to five days.

Delaware (*2017 / Regulation*) limits first-time opioid prescriptions to seven days unless the doctor determines a patient requires more. Patients receiving longer supply must undergo a physical exam and are educated about the danger of opioid abuse.

Florida (*2018 / Law*) limits opioid prescriptions for acute pain to three days, with some exceptions allowing seven days.

Hawaii (*2017 / Law*) limits first-time opioid prescriptions to seven days except for cancer patients, post-operative care patients and patients in palliative care.

Indiana (*2017 / Law*) limits first-time opioid prescriptions to seven days unless the doctor determines a patient requires more or the patient is in palliative care.

Kentucky (*2017 / Law*) limits first-time opioid prescriptions to three days unless the doctor determines a patient requires more or the patient is treated for chronic pain, cancer-related pain or post-surgery pain.

Louisiana (*2017 / Law*) limits first-time opioid prescriptions to seven days except for chronic pain patients, cancer patients, or patients receiving hospice care.

Maine (*2016 / Law*) limits first-time opioid prescriptions to seven days for acute pain and thirty days for chronic pain. Morphine milligram equivalents (MME) are limited to 100 per day except for cancer patients, hospice and palliative care patients and substance abuse disorder treatment patients.

Massachusetts (*2016 / Law*) limits first-time opioid prescriptions to seven days except for cancer pain patients, chronic pain patients, and palliative care patients.

Michigan (*2017 / Law*) limits opioid prescriptions to seven days for acute pain.

Minnesota (*2017 / Law*) limits opioid prescriptions to four days for acute dental or ophthalmic pain.

Missouri (*2017 / Regulation*) limits first-time opioid prescriptions to seven days for Medicaid recipients.

Nebraska (*2016 / Regulation*) limits opioid prescriptions to 150 doses of short-acting opioids in 30 days. In 2018, a law was passed to limit opioid prescriptions to seven days for patients under 19.

Nevada (*2017 / Law*) limits first-time opioid prescriptions to fourteen days for acute pain and 90 morphine milligram equivalents per day. Exceptions are possible, but require additional scrutiny by doctors, respectively blood and radiology tests to determine the cause of pain.

New Hampshire (*2016 / Law*) limits opioid prescriptions to seven days in an emergency room, urgent care setting or walk-in clinic.

New Jersey (*2017 / Law*) limits first-time opioid prescriptions to five days for acute pain except for cancer pain patients, hospice care patients, patients in a long-term care facility or substance abuse treatment patients.

New York (*2016 / Law*) limits first-time opioid prescriptions to seven days for acute pain except for chronic pain patients, cancer pain patients and patients in hospice or palliative care.

North Carolina (*2016 / Law*) limits first-time opioid prescriptions to five days for acute pain and seven days for post-surgery patients. Exemptions are for cancer patients, chronic pain patients, hospice or palliative care patients as well as patients being treated for substance use disorders.

Ohio (*2017 / Regulation*) limits opioid prescriptions to seven days for acute pain and an average 30 morphine equivalent does per day except for cancer patients, chronic pain patients, hospice or palliative care patients and patients treated for substance use disorders.

Oklahoma (*2018 / Law*) limits opioid prescriptions to seven days for acute pain.

Pennsylvania (*2016 / Law*) limits opioid prescriptions to seven days in emergency rooms and urgent care centers except for cancer patients, chronic pain patients and hospice and palliative care patients.

Rhode Island (*2016 / Law*): limits opioid prescription to 30 morphine milligram equivalents per day for a maximum of 20 doses except for cancer pain patients, chronic pain patients and hospice and palliative care patients.

South Carolina (*2018 / Regulation*) limits first-time opioid prescriptions to five days or 90 morphine milligram equivalents per day except for cancer pain patients, chronic pain patients, sickle cell disease-related patients, palliative care patients and substance abuse disorder treated patients.

Tennessee (*2018 / Law*) limits first-time opioid prescriptions to three days, but allows for ten and thirty day prescriptions if certain requirements are met.

Utah (*2017 / Law*) limits first-time opioid prescriptions to seven days for acute pain except for complex or chronic conditions patients

Vermont (*2017 / Regulation*) sets opioid limits for minor, moderate, severe and extreme pain. Adults suffering from moderate pain are limited to 24 morphine milligram equivalents per day and with severe pain to 32 morphine milligram equivalents per day.

Virginia (*2017 / Regulation*) limits opioid prescriptions to seven days for acute pain and 14 days for post-surgical pain except under extenuating circumstances.

Washington (*2017 / Law*) limits opioid prescriptions for Medicaid patients under the age of 20 to 18 tablets and for patients 21 years and older to 42 tablets, equivalent to about a seven day supply. Limits can be exceeded if deemed necessary by the prescriber and do not apply to cancer patients as well as hospice and palliative care patients.

West Virginia (*2018 / Law*) limits opioid prescriptions to seven days for short-term pain, four days for emergency room prescriptions and three days for prescriptions by a dentist or optometrist except for cancer patients, hospice patients and nursing home/ long/term care patients.

C.3.2 Difference-in-differences estimates: opioid laws and regulations

Table C.IV. Sun and Abraham (2021a): Estimates for the effect of opioid laws on prescriptions and home values

The sample period is 2013 to 2018. The dependent variable is total county prescription in Panel A and the log percentage change in average county home values in Panel B. We estimate a two-way fixed effects (FE) regression with relative time treatment dummies based on the passage of the law in column 1 as well as Sun and Abraham (2021a)'s interaction weighted (IW) regression in columns 2 to 5. Column 2 reports the sample share weighted average of the $CATT$ in columns 3 to 5. County controls include the male population ratio, White ratio, Black ratio, American-Indian ratio, Hispanic ratio, age 20-64 ratio, age over 65 ratio, migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, neoplasm mortality, and physicians. In Panel A, we additionally include log total population as control. Standard errors are clustered at the state level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

Panel A: Dependent Variable: Total County Prescriptions

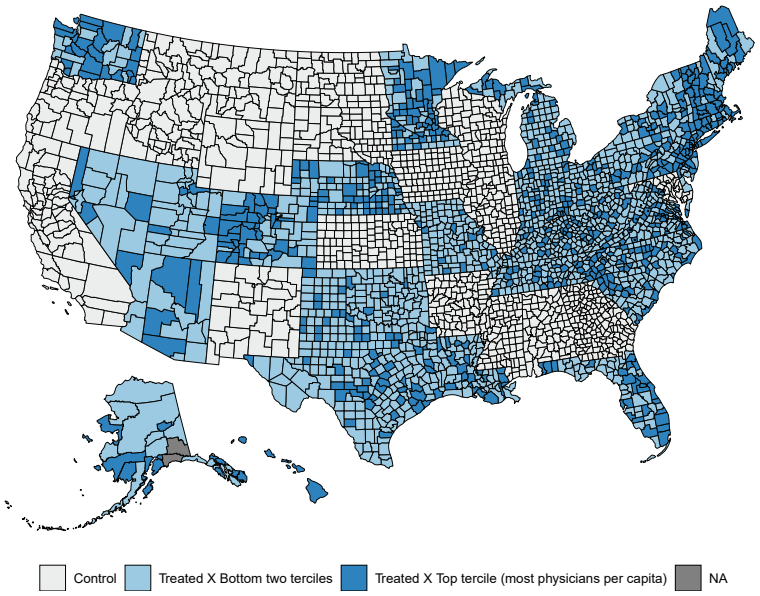
Year Relative To	Fixed Effect	Interaction Weighted			
Legislation	Total	Total	CATT Treat-year 2016	CATT Treat-year 2017	CATT Treat-year 2018
-5	2689.698	3497.861			3497.861
	(3056.589)	(3427.335)			(3427.335)
-4	1157.515	2151.615		2176.786	2071.731
	(1947.820)	(1407.503)		(1559.227)	(3165.726)
-3	860.781	1341.518	595.802	1485.804	1448.472
	(1297.242)	(1022.672)	(2522.228)	(1244.869)	(2484.415)
-2	581.373	1017.781	-585.046	1507.798**	676.753
	(841.488)	(668.658)	(2617.587)	(748.834)	(1136.858)
-1	0.000	0.000	0.000	0.000	0.000
0	-2702.161***	-2662.167***	-5339.808***	-2405.188**	-1449.456
	(1017.822)	(870.132)	(1900.458)	(1210.829)	(1253.547)
1	-7006.290***	-6136.949***	-13886.934***	-4287.188*	
	(2512.969)	(2056.392)	(4490.847)	(2310.707)	
2	-18439.869***	-19745.131***	-19745.131***		
	(5731.248)	(5496.416)	(5496.416)		

Panel B: Dependent Variable: Percentage Change in Average County Home Value

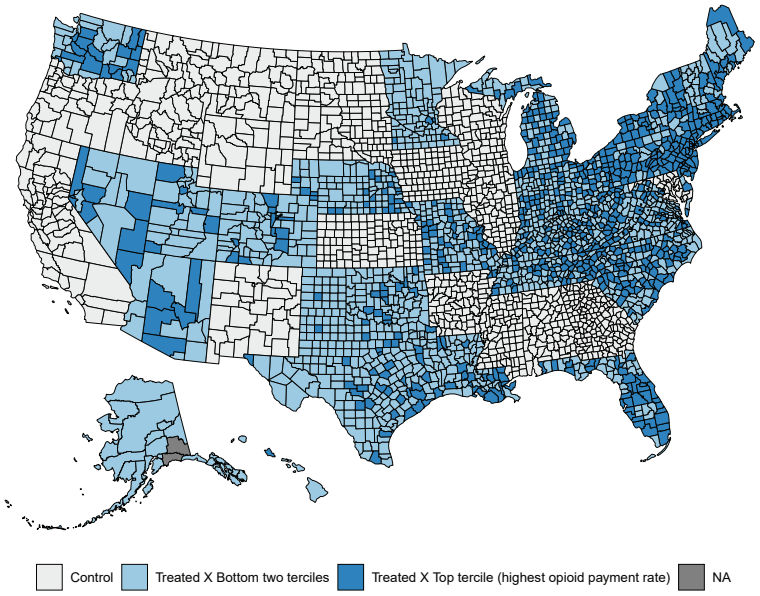
Year Relative To	Fixed Effect	Interaction Weighted			
Legislation	Total	Total	CATT Treat-year 2016	CATT Treat-year 2017	CATT Treat-year 2018
-5	-0.584	-0.471			-0.471
	(1.014)	(1.080)			(1.080)
-4	-0.405	-0.506		-0.495	-0.539
	(0.555)	(0.522)		(0.638)	(0.801)
-3	-0.166	-0.342	0.530	-0.680	0.070
	(0.380)	(0.375)	(0.692)	(0.528)	(0.574)
-2	0.016	-0.056	-0.151	-0.114	0.198
	(0.176)	(0.185)	(0.473)	(0.248)	(0.285)
-1	0.000	0.000	0.000	0.000	0.000
0	0.437***	0.423***	0.549**	0.465**	0.193
	(0.153)	(0.160)	(0.222)	(0.200)	(0.436)
1	0.954***	0.810***	1.418***	0.665*	
	(0.302)	(0.302)	(0.304)	(0.367)	
2	1.664***	1.781***	1.781***		
	(0.360)	(0.382)	(0.382)		

Figure C.VI. Interaction of opioids laws with supply propensity dummies

We visualise the realtive treatment intensity within a state based on total physicians per capita in Panel A and physician opioid payment in Panel B. Control states/counties are coloured in grey. Treated states in the bottom two terciles based on either measure are coloured in light blue. Treated sates in the top terciel based on either measure, i.e. those where the treatement was strongest, are colored in dark blue.



(a) Top physicians per capita tercile



(b) Top physician opioid payment rate tercile

Table C.V. Opioid Law Impact on prescription and home values around state borders: No controls

The unit of observations are counties. In columns 1 to 4 we consider all counties. In columns 5 to 8 we exclude counties with more than 8 pill mills. We calculate one or two-year difference in prescription rate, respectively percentage changes in home values from the treatment year - 1 to the treatment year, respectively treatment year + 1. For control counties, we calculate the difference, respectively percentage change from 2015 to 2016 or 2017, as the first law was passed in 2016. We do not include additional control variables. We follow Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth. Standard errors are clustered at the state level. $***$ indicates p ¡ 0.01, $**$ indicates p ¡ 0.05, and $*$ indicates p ¡ 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All counties				Excluding pill mill counties			
	Difference in County Prescription Rates over ...							
	1 year		2 years		1 year		2 years	
RD Estimate	-4.101***	-3.963***	-2.524	-2.286	-3.938***	-3.819**	-2.361	-2.105
	(1.363)	(1.410)	(2.531)	(2.599)	(1.430)	(1.488)	(2.674)	(2.750)
Observations	2725	2725	2375	2375	2546	2546	2232	2232
MSEBandwidth	104	191	117	203	104	189	118	202
Effective LHS Obs	644	944	691	955	624	895	673	915
Effective RHS Obs	684	1075	567	848	646	1004	541	793
Polynominal Order	1	2	1	2	1	2	1	2
	Percentage Change in County Average Home Values over...							
	1 year		2 years		1 year		2 years	
RD Estimate	1.338*	1.307*	2.622**	2.638*	1.358*	1.384*	2.671**	2.762**
	(0.760)	(0.785)	(1.299)	(1.355)	(0.755)	(0.766)	(1.284)	(1.313)
Observations	2551	2551	2217	2217	2374	2374	2076	2076
MSEBandwidth	134	233	151	232	125	227	143	230
Effective LHS Obs	676	872	733	871	629	826	678	827
Effective RHS Obs	821	1203	672	910	729	1109	612	854
Polynominal Order	1	2	1	2	1	2	1	2

C.3.3 Overdose death rate variables

As Li and Zhu (2019), we rely on the public-use mortality data that captures drug overdose mortality. These data is censored, suppressing counties with less than 10 deaths. To address the censorship issue, we first impute missing annual death rate from 2-year death rates and annual death rates. This allows us to impute below 10 death rates for annual death rates that follow or are followed by annual death rates' above 10. We also consider 3-year death counts, as this substantially increases the number of counties covered. The 10 death cut-off is now aggregated across three years. For both the annual as well as the 3-year death counts, we calculate overdose death rates per 100,000 residents. The 3-year death rate accounts for 3 years of county population.

Finally, we construct a dummy to capture counties in the top tercile of the 3-year death rate. This allows us to impute the maximum death rate of previously suppressed counties. By definition, the maximum number of deaths of suppressed observations is 9 which allows us to calculate a maximum death rate. Counties that fall into the bottom two terciles with the "maximum" death rate will be part of the bottom two terciles with their true death rate as well, which is lower or equal to the maximum death rate. However, we cannot stop after this first iteration, as counties whose imputed maximum death rate may actually be lower and therefore push counties within the bottom two terciles above the cutoff. We therefore first drop counties that are in the top tercile with their imputed death rate, as we cannot assign these counties with certainty. Next, we repeat the tercile construction in an iterative way, dropping of top-tercile imputed counties until we are only left with imputed counties at the bottom two terciles. This allows us to substantially increase observations and address the censorship issue. We end up with three alternative opioid overdose death measures.

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