

Applications of Endogenous Information Acquisition by Institutional Investors

Thesis Submitted for the Degree: PhD

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JEL classification: G14, G23, G30.

Keywords:

Information Acquisition

Macroeconomic Announcements

Informational Efficiency

Institutional Investors

Corporate Governance

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Declaration of Originality

I would like to declare that my doctoral thesis is based on my doctoral studies at Imperial College London and is my own. The work reflecting other people's research is appropriately referenced.

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Abstract

Acquiring information consumes investors' learning capacity, a valuable and limited resource that requires optimal allocation.

Chapter One theoretically explores and empirically examines the roles of macroeconomic announcements when investors digest firm-earnings news. Macroeconomic announcements can distract investors upon being released if information about the aggregate risk competes with firm-earnings news to occupy investors' learning capacity. However, valuable information about the aggregate risk is disclosed to the general public via these announcements, temporarily lifting the burdens on investors to privately acquire such information and therefore leaving them more learning capacity to process firm-specific information.

Combining these competing views, this chapter incorporates the releases of macroeconomic announcements into a rational inattention framework, and proposes the “*attention re-allocation mechanism*” to understand their effects on informational efficiency of individual firms. This mechanism confirms the distracting effects of macroeconomic announcements prior to being released and their complementary effects upon being released. This framework further predicts that these effects are more (less) pronounced during expansions (recessions). Empirical evidence is provided to support model predictions.

Chapter Two revisits information acquisition theory from a corporate governance perspective. In this chapter, I provide a rational expectations framework to model monitoring and information acquisition and explore their within-firm and cross-firm interactions. My model proposes the “monitoring-for-learning” mechanism to describe that investors optimally *re-allocate* monitoring effort from firms with low value of information acquisition to firms with high value of information acquisition. This mechanism has empirical implications for information acquisition: Institutional investors tend to acquire more precise information about the firms they can more effectively engage with and about those they have larger holdings in. **Chapter Three** provides empirical evidence to support model predictions in Chapter Two.

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0. Introduction

Chapter One theoretically explores and empirically examines the roles of macroeconomic announcements when investors digest firm-earnings news. Macroeconomic announcements reveal valuable information to the general public and have aggregate-level implications for financial markets.¹ Recent empirical research suggests a complementary relation between these announcements and informational efficiency of individual stocks.² Arguably, macroeconomic announcements may distract investors' attention if they contain information about the aggregate risk that competes with firm-earnings news to occupy investors' learning capacity. However, relevant information about the aggregate risk is disclosed to the general public via these announcements, temporarily lifting the burdens on investors to privately acquire such information. Consequently, upon receiving this public information, investors with a fixed learning capacity can temporarily shift their attention from the aggregate risk to firm-specific risks.

Clearly, there is lack of formal theoretical framework to jointly consider these two competing features of macroeconomic information, especially when exploring their empirical implications on how stock markets process firm-specific information. A simple framework of rational inattention is able to reflect the distracting feature of macroeconomic news. Nonetheless, it may ignore the complementary feature to a large extent. A model that accommodates both features can suggest via what mechanism macroeconomic announcements influence informational efficiency of individual firms, examine whether recent empirical findings are properly interpreted, and potentially deliver new predictions that are empirically testable.

¹For example, Ederington and Lee (1993), McQueen and Roley (1993), Flannery and Protopapadakis (2002), Beber and Brandt (2006), Savor and Wilson (2013), Lucca and Moench (2015), Chordia, Green and Kottimukkalur (2018), among many others.

²Sheng (2019) documents the complementary effects of macroeconomic news on market efficiency of individual firms. He argues that total investor attention turns temporarily higher on days of releasing macroeconomic news. He presents additional evidence against the argument of information spillover from macroeconomic news to firm-specific news.

Therefore, **Chapter One** aims to provide a theoretical framework for researchers to understand the fundamental roles of macroeconomic announcements during the process of investors digesting firm-specific information. In particular, I incorporate the release of macroeconomic information as a shock to investors' existing allocation of attention. This chapter further derives propositions and delivers new predictions regarding the differential effects of these announcements on informational efficiency of individual firms between expansions and recessions.

I propose the “attention re-allocation mechanism” to explain why and how investors re-allocate their learning capacity upon the releases of macroeconomic information. More importantly, this chapter argues that the attention re-allocation effects of releasing macroeconomic announcements are more pronounced during expansions than recessions. Intuitively, the marginal value of acquiring private information about the aggregate risk is high during recessions such that investors tend to have their capacity exhausted in learning about the aggregate risk. Even when receiving an informative signal of the aggregate risk from macroeconomic announcements, investors still largely focus on the aggregate risk and leave very little capacity to digest firm-specific information during recessions. That is, upon releasing macroeconomic information, very little attention is re-allocated from the aggregate risk to firm-specific risks during recessions.

From recessions to expansions, nonetheless, the marginal value of acquiring private information about the aggregate risk becomes lower such that investors now allocate substantial capacity to learn about firm-specific risks. Upon receiving an informative signal of the aggregate risk, investors will optimally re-allocate learning capacity to further digest firm-specific information. Eventually, during expansions, the mechanism supports a significant pattern of attention re-allocation from the aggregate risk to firm-specific risks. These attention re-allocation patterns during expansions and recessions, respectively, provide theoretical support for how informational efficiency of individual firms is endogenously determined and

differentially influenced by macroeconomic announcements along the business cycle.

Macroeconomic announcements are pre-scheduled and can arguably have distracting effects on investors of individual firms prior to being released. Valuable information about the aggregate risk is not released yet, but the aggregate risk may always compete with firm-specific risks for investors' limited attention regardless of macroeconomic information being released or not. Increases in aggregate volatility prior to macroeconomic announcements disruptively raise the marginal value of acquiring more precise information about the aggregate risk, bringing a good playfield to examine the attention re-allocation mechanism I propose in this chapter.³ Briefly, pre-scheduled macroeconomic announcements can distract investor attention from collecting private firm-specific information.

Empirically, **Chapter One** presents evidence to support core model predictions that the complementary effects of macroeconomic announcements on digesting firm-earnings news are more pronounced during expansions than recessions. During expansions, immediate price responses are 7.30% larger and delayed price responses are 79.05% smaller on days with macroeconomic announcement. Nonetheless, during recessions, I find no statistical significance for such complementary effects of macroeconomic announcements on informational efficiency of individual firms. I conduct additional tests using alternative windows of cumulative abnormal returns (CAR) or alternative ways to generate CARs for robustness check.

Next, empirical findings of the pre-earnings-announcement drifts (PreEADs) further confirm the distracting effects of pre-scheduled macroeconomic news via the attention re-allocation mechanism I propose in the model. I decompose PreEADs into (i) share price response to analyst earnings forecast consensus, "*REF*", and (ii) share price response due to investors' private information, "*InvestorPI*". I find that both price responses are statistically significantly associated with the to-be-announced earnings news in the same direction in both

³Suggestive evidence for such disruptive increases in aggregate volatility will be provided when motivating the theoretical framework in Section 1.2.

the full sample and the subsample of expansions. However, I find no statistical significance for the association between investors' private information and the to-be-announced earnings news during recessions.

These results suggest that investors rely on both analyst earnings forecasts and their private information in the pre-earnings-announcement period during expansions. During recessions, however, investors do not acquire (much) private information about the to-be-announced earnings news. Instead, they simply follow analyst earnings forecasts during recessions. These empirical findings not only support model predictions but also underscore the importance of using an endogenous information acquisition framework to understand time-varying informational efficiency of individual firms.

Finally, I find that pre-scheduled releases of macroeconomic information have distracting effects on PreEADs. Using the whole sample, these distracting effects persist even after separately considering share price responses to analyst earnings forecast consensus and to investors' private information, respectively. Specifically, I find that PreEADs are 30.81% smaller, *REF* 25.87% smaller, and *InvestorPI* 43.98% smaller when there are macroeconomic announcements pre-scheduled to be released on the same day with a firm's earnings announcement. Not surprisingly, subsample analyses suggest that these distracting effects of macroeconomic announcements are statistically significant only during expansions, with PreEADs being 36.64% smaller, *REF* 26.11% smaller, and *InvestorPI* 59.37% smaller.

During recessions, however, I find no statistical significance for such distracting effects of macroeconomic announcements on PreEADs, *REF*, or *InvestorPI*. Consistent with model predictions, these subsample analyses complement previous empirical work that exclusively focuses on immediate and delayed price responses when evaluating informational efficiency of individual stocks. In particular, empirical evidence regarding *InvestorPI* in expansions versus recessions directly speaks to the endogenous information acquisition behavior in dif-

ferent states of the business cycle. These subsample analyses further confirm time-varying informational efficiency as featured in the model where investors endogenously acquire firm-specific private information and optimally re-allocate attention between the aggregate risk and firm-specific risks.

Chapter Two theoretically revisits information acquisition theory from a corporate governance perspective. Institutional ownership in US public equity markets has steadily increased over the past few decades. How institutional investors engage with corporate management and conduct independent research⁴ to acquire non-public information about portfolio firms has attracted substantial interest from academics and practitioners. To fulfil their fiduciary duty to beneficiary owners, institutional investors monitor portfolio firms and discipline corporate executives, which eventually enhances firm fundamental values.⁵ Besides, institutional investors are sophisticated professionals that have been documented to collect non-public information and make well-informed portfolio choices or trading decisions.

Monitoring and information acquisition, both occupying valuable resources of time and personnel, are considered in various settings as interchangeable terms to shareholder attention, or investor attention in general, depending on the context under discussion. For example, investor attention in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) refers to learning capacity.⁶ Shareholder attention in Kempf, Manconi and Spalt (2017) actually refers to shareholders' monitoring pressure on firm managers.⁷ Therefore, in principle, monitoring and information acquisition are conceptually two different things and actually influence dif-

⁴“Conducting independent research” in this chapter refers to privately learning about firm fundamentals via processing and analyzing firm-specific information without directly engaging with corporate executives.

⁵“Monitoring” in this chapter refers to improving corporate governance and performance through proactively engaging with corporate executives and the board of directors, and responsibly voting at annual general meetings. Such engagement and responsible ownership demand transparency and feasibility in remuneration policies, independence and diversity of the board, and accountability of board members and executives (Hermes (2012, 2013, 2017)).

⁶They provide a model to describe how US mutual fund managers optimally re-allocate their learning capacity between the aggregate risk factor and firm-specific risks over the business cycle.

⁷They provide firm-level evidence to argue for the disciplining effects of monitoring pressure on firm managers in terms of corporate actions.

ferent aspects of a standard portfolio choice problem: Improving firm fundamentals raises a firm’s expected payoff and learning about firm fundamentals reduces uncertainty about that firm.

Establishing a clear distinction between monitoring and information acquisition has been largely ignored in previous studies. Prior literature conventionally assumes an investor is equally informed about all firms she holds. In consequence, it is fairly difficult for researchers to look inside an investor’s portfolio and study why she can be differentially informed about subgroups of firms within her portfolio. Similarly, it is challenging to study why subgroups of investors for a given firm are differentially informed about this firm.

In this chapter, I theoretically distinguish between monitoring and information acquisition with two underlying assumptions to better understand how they interact with each other. More importantly, this theoretical framework helps explain why determinants of making monitoring effort matter for investors’ information acquisition activities and deliver new predictions for information acquisition theories. My model predicts a cross-sectional “re-allocation” pattern of monitoring effort within an investor’s portfolio and provides empirical evidence to support this prediction. Regarding the implications for information acquisition, my model suggests that investors tend to have more precise information about the firms they can more effectively engage with and about the firms they have larger initial holdings in. Supportive empirical evidence is provided for these model predictions.

In **Chapter Three**, I provide empirical evidence for the re-allocation pattern of monitoring effort as suggested under the monitoring-for-learning mechanism of **Chapter Two**. This mechanism indicates that shocks to other firms’ ex-ante volatility matter for an investor’s optimal monitoring effort; thus, optimal monitoring effort is predicted to be negatively correlated with how distracted a firm’s investors are due to shocks to other firms’ ex-ante volatility. Using firm-level distraction score in Kempf, Manconi and Spalt (2017) and using

contested voting activities at annual general meetings (AGMs) as proxy for firm-level endogenous monitoring effort, I find that contested voting activities at AGMs are less likely to occur among firms with largely distracted shareholders. I also find that contested voting activities at AGMs are more likely to occur among the firms investors can more effectively engage with. These findings provide direct empirical evidence regarding the properties of optimal monitoring effort and the monitoring-for-learning mechanism as solved in the model.

Finally, I conduct direct tests on within-firm complementarity between monitoring and information acquisition. This within-firm complementarity indicates stock-picking ability change negatively in response to reduced monitoring intensity at investor-firm level. Specifically, using the investor-specific component of firm-level distraction score as in Kempf, Mancini and Spalt (2017), I find that investors tend to have a lower score of stock-picking ability if monitoring intensity on a given firm is largely reduced. I also check the first difference of stock-picking ability and find that change in stock-picking ability is negatively correlated with reduced monitoring intensity at investor-firm level. These empirical tests further confirm the structural link between monitoring and information acquisition as assumed in the model setup.

The rest of my doctoral thesis proceeds as follows. **Chapter 1** sets up the theoretical framework, develops propositions and the associated predictions, and provides empirical evidence to argue for the distracting and complementary effects of macroeconomic announcements on informational efficiency of individual firms. **Chapter 2** models the link and distinguishes between monitoring and learning, derives propositions and conducts model robustness checks with alternative theoretical setups. **Chapter 2** also delivers empirically testable predictions and constructs empirical measures for their model counterparts. **Chapter 3** provides empirical evidence to support model predictions, and my thesis concludes.

1. Chapter One

1.1. *Related Literature and Contributions*

This chapter contributes to the theoretical literature on costly private information acquisition in general (Grossman and Stiglitz (1980), Verrecchia (1982)) and investor rational inattention in particular (Sims (2003), Van Nieuwerburgh and Veldkamp (2009, 2010), Mondria (2010)). Following Kacperczyk, Van Nieuwerburgh and Veldkamp (2016), my work focuses on the empirical implications of information acquisition theory and provides evidence to support model predictions. Furthermore, my work presents motivating evidence and incorporates the releases of macroeconomic announcements into the model as shocks to investors' attention allocation. This setup facilitates empirical tests on the theoretical framework of rational inattention by examining the attention re-allocation effects of macroeconomic announcements.

This chapter also contributes to the growing empirical literature about limited investor attention. One stream in this literature investigates the impacts of investors' limited attention on stock price responses to earnings surprises. Hirshleifer, Lim and Teoh (2009) argue that firm-earnings news announced together with a greater number of other firms announcing their earnings within the same day is more likely to face distracted investors. They document smaller immediate price responses and larger delayed price responses to earnings announcements that are accompanied with larger numbers of other firms announcing their earnings on the same day. Their findings are consistent with a framework where investors have a fixed capacity to process firm-specific information and this capacity has to be allocated among all firms announcing earnings within the same day.

Similarly, DellaVigna and Pollet (2009) argues that firm-earnings news announced on Fridays is more likely to face distracted investors than on other trading days. They provide empirical evidence that immediate price responses are smaller and delayed price responses

are larger for firm-earnings news announced on Fridays. My work joins these papers by presenting empirical evidence to confirm the effects of investor attention on market price responses to firm-earnings news. This chapter models changes in investor attention to individual firms as the learning capacity re-allocated between the aggregate risk and firm-specific risks. Furthermore, my work argues for the differential effects of investor attention on firms' informational efficiency between expansions and recessions and provides empirical evidence for these differential effects.

Another stream in this literature focuses on empirical implications of limited investor attention, or rational inattention, for mutual fund holdings or corporate governance issues. For example, Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) provide an N-risky-asset framework of endogenous information acquisition to describe how mutual fund managers optimally re-allocate their attention between the aggregate risk and firm-specific risks in different states of the business cycle. Using observable states of the business cycle, they argue that investors with limited learning capacity tend to focus more on the aggregate risk during recessions and more on firm-specific risks during expansions. Their empirical evidence suggests US mutual funds are better able to pick individual stocks during expansions and better able to time the market during recessions.⁸

Another example is Kempf, Manconi and Spalt (2017). The authors empirically identify a source of feasibly exogenous variations in investor monitoring pressure on individual firms. They argue that shocks to other firms within an institutional investor's portfolio can be distracting, shifting this investor's attention to these other firms. Their empirical evidence indicates that corporate actions exhibit "market-timing" behavior in the sense that adverse actions are associated with reduced monitoring pressure from institutional investors.⁹ My work contributes to this literature by using pre-scheduled macroeconomic announcements

⁸Kacperczyk, Van Nieuwerburgh and Veldkamp (2014) is referred to for more empirical evidence.

⁹The authors cover a variety of corporate actions, namely, M&A announcements, CEO stock option grants, dividend cuts, and CEO turnover.

as shocks to investors' endogenous choices of information acquisition and deriving firm-level empirical implications for informational efficiency.

Besides, this chapter contributes to the vast literature on earnings response coefficient (ERC). Following Collins and Kothari (1989), numerous papers investigate the factors that affect how stock price changes in response to earnings surprises (Choi and Jeter (1992), Imhoff and Lobo (1992), Teoh and Wong (1993), Dhaliwal and Reynolds (1994), Billings (1999), Hackenbrack and Hogan (2002), Ghosh, Gu and Jain (2005), Keung, Lin and Shin (2010), Mian and Sankaraguruswamy (2012), Chi and Shanthikumar (2017), and many others). My work joins this literature but focuses on the informational efficiency perspective instead to explain the time-varying feature of changes in firms' ERC due to releases of macroeconomic announcements along the business cycle.

Finally, my work is related to the literature about the price impacts of macroeconomic announcements on aggregate stock market indices, and exchange-traded funds or futures derived from market indices (McQueen and Roley (1993), Flannery and Protopapadakis (2002), and Savor and Wilson (2013), Chordia, Green and Kottimukkalur (2018), and Kurov, Sancetta, Strasser and Wolfe (2019)).¹⁰ This chapter focuses on empirical implications of macroeconomic information for individual firms. In particular, my empirical evidence discusses the distracting and complementary roles of macroeconomic announcements prior to and upon being released, respectively, when investors endogenously choose to acquire private information about individual firms. My work also complements this literature by theoretically establishing the mechanism through which macroeconomic announcements can affect stock price of individual firms.

¹⁰Savor and Wilson (2014) and Andrei, Cujean and Wilson (2018) provide detailed discussions on the empirical evidence and theoretical foundation for CAMP to hold on days with pre-scheduled macroeconomic announcements. Resolution of macroeconomic uncertainty on such days is suggested as one candidate interpretation of their results.

The rest of this chapter proceeds as follows. Section 1.2 motivates and sets up the model. Section 1.3 introduces the empirical framework and links the model with empirically testable predictions. Section 1.4 presents major empirical findings for further discussions. Section 1.5 conducts various robustness checks, and Section 1.6 summarizes this chapter.

1.2. *The Model with Two Competing Features*

1.2.1. *Basic Model Setup*

The theoretical framework starts with Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) as a building block. The basic model setup reflects the distracting feature of macroeconomic announcements in the sense that they contain information about the aggregate risk that competes with firm earnings news to occupy investors' learning capacity. There is one riskfree asset with a gross rate r . The price of the riskfree asset is normalized to 1. There are N risky assets with payoffs $\tilde{V}_i$, $i = 1, \dots, N$. The first $N - 1$ risky assets (firms) have exposure to both firm-specific shocks $\tilde{Z}_1, \dots, \tilde{Z}_{N-1}$, and the aggregate shock $\tilde{Z}_N$. Assume all shocks are normally distributed with zero mean: $\tilde{Z}_i \sim \mathcal{N}(0, \sigma_i)$, $i = 1, \dots, N$. In particular, for firms $i = 1, \dots, N - 1$,

$$\tilde{V}_i = \bar{V}_i + b_i \tilde{Z}_N + \tilde{Z}_i \quad (1)$$

where $\bar{V}_i$ is firm i 's unconditional expected payoff, and b_i is firm i 's loading of exposure to the aggregate shock $\tilde{Z}_N$.¹¹ The N^{th} risky asset has no exposure to any firm-specific shocks; instead, it has a unit loading of exposure to the aggregate shock. That is,

$$\tilde{V}_N = \bar{V}_N + \tilde{Z}_N \quad (2)$$

¹¹Firms $i = 1, \dots, N - 1$ are assumed to have a unit loading of exposure to their own firm-specific shock and a zero loading of exposure to other firms' shocks as in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016).

There is a continuum of investors with mass one, CARA preference and risk aversion ρ . Investor $j \in [0, 1]$ faces a fixed learning capacity, K_j , to be optimally allocated across all N risk factors, including both the aggregate risk and firm-specific risks. Let K_{ij} denote the learning capacity allocated to $\tilde{Z}_i$ by investor j for $i = 1, \dots, N$. Allocating learning capacity to a risk factor in rational expectations models can be considered as receiving a private signal, about that risk factor, with a zero mean and a variance inversely proportionate to the amount of allocated learning capacity. The more capacity allocated to a risk factor, the more precise signal received by investor j . Let $\tilde{\theta}_{ij} = \tilde{Z}_i + \epsilon_{ij}$ denote the private signal of risk factor i received by investor j , where ϵ_{ij} is a mean-zero noise in investor j 's private signal. Allocating a learning capacity of K_{ij} to risk factor i means $\epsilon_{ij} \Big| \tilde{Z}_i \sim \mathcal{N}(0, \frac{1}{K_{ij}})$. The linear learning capacity constraint of investor j takes the form¹²:

$$\sum_{i=1}^N K_{ij} \leq K_j \quad (3)$$

A “no-forgetting” constraint is in need to rule out the possibility that investors intentionally choose to forget some prior common knowledge. Without directly modelling the releases of macroeconomic announcements, the no-forgetting constraint takes the form:

$$K_{ij} \geq 0 \quad (4)$$

for $i = 1, \dots, N$. Forgetting prior common knowledge is unrealistic because an information signal cannot have a negative variance.

It is a static model with four time points. At $t = 0$, investor j has common knowledge about these risky assets. The unconditional normal distributions of Z_i , $i = 1, \dots, N$ are common knowledge. At $t = 1$, investor j would need to optimally allocate her learning

¹²Entropy-based constraints of learning technology are checked in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) and Zhang (2019). K_j allows for heterogeneous capacity among investors $j \in [0, 1]$; however, this static model speaks to the assumption that investor j 's learning capacity remains constant over time, or at least changes slowly.

capacity among the aggregate risk and firm-specific risks. Investor j essentially chooses which firm's information to acquire and how precise she would like the information to be, and this applies to the aggregate risk as well.¹³ At $t = 2$, investor j makes her optimal portfolio choice conditional on her information choice at $t = 1$. Finally, at $t = 3$, payoffs and utility are realized.

This static model is solved using backward induction in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Equilibrium prices for all risk factors, $\tilde{p} = (p_1, \dots, p_N)'$, are determined by equating supply and demand of firm shares. The supply of each risk factor is normalized to 1 such that investor j 's optimal portfolio choice $q_j = (q_{1j}, \dots, q_{Nj})'$ can be considered as percentage of risk factors $\tilde{Z} = (\tilde{Z}_1, \dots, \tilde{Z}_N)'$. Conventionally, noise traders are assumed to submit random orders $x = (x_1, \dots, x_N)'$.¹⁴ This is to prevent equilibrium prices from fully revealing investors' private information.

Investor j 's terminal wealth W_j takes the form:

$$W_j = rW_0 + q_j' (\tilde{Z} - \tilde{p}r) \quad (5)$$

Investor j choose q_j to maximize time-2 expected utility U_{2j} :

$$U_{2j} = E_j(W_j) - \frac{\rho}{2} Var_j(W_j) \quad (6)$$

where $E_j(W_j)$ and $Var_j(W_j)$ are the conditional expectation and variance conditioning on investor j 's information choices at time 1. Maximizing (6) subject to (5) delivers the optimal

¹³Investor j cannot choose the level of the signal she is to observe for a certain risk factor; instead, she can choose the signal's precision. Allocating more learning capacity to a risk factor is equivalent to acquiring more precise information about this risk factor.

¹⁴ x_i has zero mean with variance σ_x and x_i 's are cross-sectionally uncorrelated.

demand for risk i from investor j :

$$q_{ij} = \frac{E_j(\tilde{Z}_i) - rp_i}{\rho \text{Var}_j(\tilde{Z}_i)} \quad (7)$$

The market clearing condition takes the form:

$$\int_0^1 q_j dj = \mathbf{1} + x \quad (8)$$

To simplify notations, define $\alpha_i = \frac{1}{\sigma_i}$ for $i = 1, \dots, N$ and $\gamma = \frac{1}{\sigma_x}$.

Let K_{ij}^O denote investor j 's learning capacity allocated to firm $i = 1, \dots, N - 1$, and K_{Nj}^O to the aggregate risk, both subject to constraints (3) and (4).¹⁵ Then, let $\bar{K}_i^O = \int_0^1 K_{ij}^O dj$ denote the average learning capacity allocated to firm-specific risks for $i = 1, \dots, N - 1$, and $\bar{K}_N^O = \int_0^1 K_{Nj}^O dj$ the average learning capacity allocated to the aggregate risk. The average learning capacity allocated to a firm-specific risk directly speaks to the informational efficiency of a particular firm and is micro-founded by individual investors' information acquisition behavior.

Lemma 1.1. Equilibrium price for risk factor $i = 1, \dots, N$ takes the form:

$$p_i^* = \frac{1}{r} \left(\frac{\left(\bar{K}_i^O + \frac{(\bar{K}_i^O)^2}{\rho^2} \gamma \right) \tilde{Z}_i - \left(\frac{\bar{K}_i^O}{\rho} \gamma + \rho \right) (1 + x_i)}{\alpha_i + \bar{K}_i^O + \frac{(\bar{K}_i^O)^2}{\rho^2} \gamma} \right) \quad (9)$$

Detailed solutions to all lemmas and propositions are provided in the appendix. One major methodological contribution of Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) is to transform the joint optimal choices of information acquisition and portfolio into a linear function of information precision choices for all risk factors. Specifically, they transform the

¹⁵The optimal allocation of attention subject to constraints (3) and (4) in this “original” equilibrium is denoted with “O”.

time-2 expected utility of investor j in (6) into a linear function of K_{ij}^O for $i = 1, \dots, N$:

$$\sum_{i=1}^N \lambda_i K_{ij}^O + \text{constant} \quad (10)$$

where $\lambda_i = \bar{\sigma}_i [1 + (\rho^2 \sigma_x + \bar{K}_i^O) \bar{\sigma}_i] + \rho^2 \bar{\sigma}_i^2$ for $i = 1, \dots, N$, and $\bar{\sigma}_i = \left(\alpha_i + \bar{K}_i^O + \frac{(\bar{K}_i^O)^2}{\rho^2} \gamma \right)^{-1}$.

Intuitively, λ_i is the marginal value of acquiring an incremental unit of information precision for risk factor i .¹⁶

Clearly, the theoretical framework in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) is not specifically developed for the purposes of understanding the role of macroeconomic announcements when investors digest firm-specific information. However, it is a useful tool to think about the effects of macroeconomic announcements on investors processing firm-specific information, because both the aggregate risk and firm-specific risks compete for a limited learning capacity.¹⁷ This basic setup is well able to describe how investors optimally allocate attention across the aggregate risk and firm-specific risks as daily tasks.

1.2.2. *Modified Constraints: Upon Releases*

This section provides a straightforward and clear idea regarding the underlying mechanisms for macroeconomic announcements to influence informational efficiency of individual firms. More importantly, new predictions regarding states of business cycle are delivered for empirical tests.

¹⁶Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) show that λ_i is increasing in σ_i and decreasing in $\bar{K}_i^O$. That is, it is more valuable to learn about the more uncertain risk, and it is less valuable to learn about a certain risk if on average more learning capacity has been allocated to this risk. This substitutability of acquiring private information is recognized in Grossman and Stiglitz (1980).

¹⁷The competing feature between the aggregate risk and firm-specific risks not only applies to days with both macroeconomic announcements and firm-earnings announcements but can apply to days right before these pre-scheduled announcements.

One key idea of the literature on public information is that releasing public information can crowd out private information acquisition.¹⁸ Put differently, government agencies making macroeconomic announcements are actually releasing information of the aggregate market conditions to the general public. However, this practice may temporarily deter market participants from acquiring private information about macroeconomic conditions. That is, releasing public information can potentially crowd out private information acquisition (Amador and Weill (2010, 2011)).

Inspired by the discussions about the crowding-out effects of public information on private information, this section aims to incorporate the releases of macroeconomic information into the framework of endogenous information acquisition. Macroeconomic announcements disclose valuable information about the aggregate economy to the general public, in particular, for free. I use a straightforward way to model macroeconomic announcements as all investors receiving a free but informative signal about the aggregate risk with a given precision $K_{MA} > 0$.¹⁹

Subject to the learning capacity constraint, when investors are less occupied with acquiring private information about the aggregate risk, they tend to allocate more attention to firm-specific risks because it is not optimal to leave learning capacity unused.²⁰ When all investors allocate more learning capacity to firm-specific risks, stock markets of individual firms tend to be more informationally efficient. Overall, this mechanism indicates complementarity between releases of macroeconomic announcements and informational efficiency of individual

¹⁸Chapter 5 of Veldkamp (2011) provides a detailed discussion about this literature.

¹⁹This signal is free in the sense that it does not occupy investor j 's own valuable resources to collect information about the aggregate risk factor. This modified version may also describe investors' attention allocation choice on days without macroeconomic announcements by setting $K_{MA} = 0$.

²⁰This simplified framework may not allow for the potential existence of a principal-agent problem to reflect the fact that professional asset managers (e.g. mutual funds, pensions funds, etc.) are hired to make investment decisions on behalf of individual investors.

firms.²¹

Motivating Evidence

Prior to being released, pre-scheduled macroeconomic announcements can arguably result in disruptive increases in aggregate volatility while providing all investors with valuable information about the aggregate risk upon being released and leading to reductions in aggregate volatility. I provide preliminary evidence to motivate my modelling macroeconomic announcements for both prior to and upon being released. Following Ang, Hodrick, Xing and Zhang (2006), Barinov (2013), and Savor and Wilson (2013), I use the implied volatility of S&P 100 index option to serve as the proxy for aggregate volatility expected by the stock markets.²²

Table 1.1 presents the timing relation of daily changes in implied volatility with the pre-scheduled macroeconomic announcements. $VXO\ Change(t)$ is closing implied volatility on day t minus closing implied volatility on day $t - 1$. Columns (1) – (4) in Table 1 are OLS regressions of daily VXO changes onto indicator variables $Macroday(t)$ and $PreMacroday(t)$, and other controls where appropriate. $Macroday(t)$ equals 1 if there are macroeconomic announcements on day t , and 0 otherwise. $PreMacroday(t)$ equals 1 if there are macroeconomic announcements scheduled to release on day $t + 1$, and 0 otherwise. Panel A uses raw daily changes while Panel B winsorizes daily changes at $p=0.01$ each tail.

[Insert Table 1.1 near here]

Column (1) of Panel A in Table 1.1 shows that days with macroeconomic announcements on average experience reductions in aggregate volatility. Column (2) then shows that

²¹Sheng (2019) provides empirical evidence to argue that there are complementary effects of macroeconomic announcements on stock market efficiency of individual firms.

²²Data at the daily frequency is obtained via CBOE Indexes at WRDS. The sample period is from 1997 to 2017, inclusive. Untabulated results using VIX to serve as the proxy for aggregate volatility are checked for robustness and available upon request.

days with pre-scheduled next-day macroeconomic announcements on average experience increases in aggregate volatility. These patterns remain statistically significant when include both $Macroday(t)$ and $PreMacroday(t)$, and after further controlling for year, month, day-of-week dummies. Column (5) further includes $PostMacroday(t)$, which is defined as equal to 1 if macroeconomic announcements were announced on day $t - 1$, and 0 otherwise. This column suggests that aggregate volatility is temporarily reduced upon macroeconomic announcements and then reverted back the next day. All these results are qualitatively the same and quantitatively similar using winsorized daily changes in implied volatility.

The coefficients are of economic significance if compared with the sample standard deviation of 1.86 for raw daily changes and 1.59 for winsorized daily changes. Overall, Table 1.1 suggests the timing relation between macroeconomic announcements and aggregate volatility: Increases in aggregate volatility prior to releases of macroeconomic announcements and reductions in aggregate volatility upon releases of these announcements. These timing patterns as suggested in Table 1.1 indicate that VXO is not stationary. The level of implied volatility of S&P 100 index options is highly serially correlated (Ang et al. (2006)). In my sample, the first-order autocorrelation of VXO is 0.98, while Ang et al. (2006) find the first-order autocorrelation of VXO to be 0.94 with the sample spanning from 1986 to 2000, inclusive.

[Insert Figure 1.1 near here]

Figure 1.1 plots the level of VXO ten days before and ten days after *Macroday*. The horizontal axis is relative time, and the vertical axis is the level of aggregate volatility relative to that of *Macroday*. This figure graphically confirms reduction in aggregate volatility on *Macroday*. In the couple of days right before *Macroday*, there seems to be a transient climb up in aggregate volatility. These features regarding the level of VXO are consistent with the regression results in Table 1.1 using the first difference of VXO.

Incorporate Releases of Macroeconomic Announcements into Model

The original constraints of learning capacity and no-forgetting conditions have to be modified to incorporate K_{MA} into the model. Let K_{ij} denote investor j 's learning capacity allocated to firm $i = 1, \dots, N - 1$, and K_{Nj} to the aggregate risk, both subject to the modified constraints. Now, the new learning capacity constraint is

$$(K_{Nj} - K_{MA}) + \sum_{i=1}^{N-1} K_{ij} \leq K_j \quad (11)$$

and the new no-forgetting constraint is

$$K_{ij} \geq 0 \quad (12)$$

for firms $i = 1, \dots, N - 1$, and

$$K_{Nj} - K_{MA} \geq 0 \quad (13)$$

for the aggregate risk.²³ The rest of this section will discuss the implications of incorporating K_{MA} into the model via constraints (11) – (13).

Due to higher risk aversion and larger uncertainty of the aggregate risk during recessions, the marginal value of acquiring more precise information about the aggregate risk, λ_N , is higher during recessions than expansions.²⁴ Releases of macroeconomic announcements containing information about the aggregate risk can serve as shocks to investors' information

²³The “ $K_{Nj} - K_{MA}$ ” term in (11) and (13) suggests that any additional information about the aggregate economy on top of what has already been delivered via macroeconomic announcements comes through investor j 's learning capacity. Alternatively, this term could be interpreted as the revealed macroeconomic information that cannot be obtained by gathering firm-specific information. Presumably, this setup would have to assume the pure orthogonality between the revealed macroeconomic information and firm-specific information.

²⁴Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) shows that the marginal value of acquiring more precise information about the aggregate risk is higher when the ex-ante uncertainty of the aggregate risk is higher. Higher risk aversion during recessions amplifies this effect.

environment. How responsively investors react to these shocks and re-allocate their attention between the aggregate risk and firm-specific risks depends on the relative magnitude of λ_N and λ_i , $i = 1, \dots, N - 1$. Incorporating the releases of macroeconomic announcements into Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) enables researchers to theoretically motivate and empirically test the differential impacts of macroeconomic announcements on the attention re-allocation pattern between the aggregate risk and firm-specific risks along the business cycle.

Lemma 1.2. Let $\bar{K}_i = \int_0^1 K_{ij} dj$ denote the average learning capacity allocated to firm-specific risks for $i = 1, \dots, N - 1$, and $\bar{K}_N = \int_0^1 K_{Nj} dj$ the average learning capacity allocated to the aggregate risk. Then, $0 \leq \bar{K}_N - \bar{K}_N^O \leq K_{MA}$, and $(K_{MA} + \bar{K}_N^O) - \bar{K}_N$ is larger (smaller) when λ_N is low (high).

$(K_{MA} + \bar{K}_N^O) - \bar{K}_N$ measures the amount of learning capacity “crowded out”, or re-allocated, from the aggregate risk to firm-specific risks due to all investors receiving K_{MA} . This lemma suggests that macroeconomic announcements crowd out learning capacity from the aggregate risk to firm-specific risks. In addition, such crowding-out effects are stronger when the marginal value of acquiring more precise information about the aggregate risk is low. That is, for a fixed amount of public information contained in macroeconomic announcements, a larger amount of learning capacity is re-allocated to firm-specific risks when it is less valuable to acquire more precise information about the aggregate risk.

Proposition 1.1. The average learning capacity allocated to firm i weakly increases for $i = 1, \dots, N - 1$ upon receiving K_{MA} by all investors. This re-allocation effect is larger (smaller) when λ_N is low (high). That is,

$$[\bar{K}_i - \bar{K}_i^O]_{high-\lambda_N} \leq [\bar{K}_i - \bar{K}_i^O]_{low-\lambda_N} \quad (14)$$

for $i = 1, \dots, N - 1$.

Proposition 1.1 is the flip side of Lemma 1.2 but focuses on firm-specific risks. The total amount of learning capacity re-allocated from the aggregate risk is to be distributed to firm-specific risks. This attention re-allocation mechanism indicates that informational efficiency of individual firms can be enhanced upon all investors receiving K_{MA} . Besides, this proposition states that this attention re-allocation effect is stronger when λ_N is low (i.e. in expansions) and weaker when λ_N is high (i.e. in recessions).

1.2.3. *Pre-scheduled Macroeconomic Announcements*

Prior to being released, pre-scheduled macroeconomic announcements can be feasibly distracting to investors who are collecting private information about the to-be-announced firm-earnings news. This can result from the disruptively increased aggregate volatility before these pre-scheduled announcements. This subsection theoretically motivates the distracting feature of macroeconomic announcements prior to being released via the attention re-allocation mechanism I propose in this chapter.²⁵

Lemma 1.3. $\bar{K}_N^O$ weakly increases and $\bar{K}_i^O$ weakly decreases, $i = 1, \dots, N - 1$, in response to an exogenous increase in σ_N .

This lemma states that an increased aggregate volatility leads to an increased learning capacity allocated to the aggregate risk and a decreased learning capacity allocated to any firm-specific risk. Subject to the learning capacity constraint, the sum of decreases in the learning capacity for firm-specific risks is exactly the amount of increased learning capacity for the aggregate risk.

²⁵This subsection essentially provides comparative statics for the optimal allocation of learning capacity in the original equilibrium.

Proposition 1.2. Let σ'_N denote the exogenously increased σ_N by a discrete unit. Then,

$$[\bar{K}_i^O(\sigma_N) - \bar{K}_i^O(\sigma'_N)]_{high-\lambda_N} \leq [\bar{K}_i^O(\sigma_N) - \bar{K}_i^O(\sigma'_N)]_{low-\lambda_N} \quad (15)$$

for $i = 1, \dots, N - 1$.

This proposition states that the learning capacity re-allocated from a firm-specific risk to the aggregate risk is small (large) when λ_N is high (low).²⁶ Notably, both Lemma 1.3 and Proposition 1.2 emphasize the re-allocative feature of the learning capacity constraint: The aggregate risk competes with firm-specific risks for a fixed learning capacity. Lemma 1.3 focuses on the level of learning capacity allocated to a risk factor, while Proposition 1.2 focuses on the change in learning capacity allocated to a firm-specific risk due to an increase in the aggregate volatility. This re-allocative feature underlies the distracting effect of a disruptive increase in aggregate volatility on the average learning capacity allocated to firm-specific risks.

1.3. *Bring the Model to Data*

1.3.1. *Empirical Framework*

The empirical section of this chapter focuses on the implications of investors' information acquisition behavior on informational efficiency of individual firms. To link the theoretical framework with its empirical counterparts, the empirical framework aims to explore the pricing dynamics around the quarterly earnings announcements. Specifically, my work focuses on the window from $t = -15$ days to $t = +15$ days with $t = 0$ being a firm's earnings announcement date. A firm is more informationally efficient if its investors on average allocate more learning capacity to this firm (i.e. high $\bar{K}_i$). Informational efficiency of individual

²⁶Proposition 1.2 speaks to the model prediction that pre-scheduled macroeconomic announcements have distracting effects on investors before the releases of firm earnings announcements and same-day macroeconomic announcements and that such distracting effects are more pronounced during expansions (low λ_N) than recessions (high λ_N).

firms upon earnings announcements is jointly measured by two dimensions, namely, immediate price response and delayed price response.²⁷ For a given level of earnings surprises, larger immediate price responses and smaller delayed price responses jointly suggest a firm's stock market is more informationally efficient.

Immediate price responses are measured by the two-day cumulative Fama-French 3-factor abnormal return, $CAR(0, 1)$. Delayed price responses are measured by the cumulative Fama-French 3-factor abnormal return in the window $[2, 15]$ days after a firm's quarterly earnings announcement, $CAR(2, 15)$. Other measures of immediate and delayed price responses generated via alternative pricing models or event windows are considered for robustness check. Earnings surprises are measured by the difference between a firm's actual end-of-quarter earnings and analyst earnings forecast consensus. Following Dellavignall and Pollet (2009), 11 quantiles of standardized unexpected earnings are generated where quantile 6 is for zero earnings surprises, quantiles 1 – 5 for negative earnings surprises, and quantiles 7 – 11 for positive earnings surprises.

Each observation of earnings announcement is linked with another two variables that specify (1) whether there is a macroeconomic announcement released on the same day, and (2) whether the macroeconomy is recessionary or expansionary. Observations with macroeconomic announcements are modelled as all investors receiving a free signal of precision K_{MA} about the aggregate risk. Observations in a recessionary macroeconomic environment are modelled as having a high λ_N , where λ_N is weakly increasing in σ_N and ρ , respectively.²⁸ Using states of the business cycle, jointly with the pricing dynamics around earnings announcement, is the very key feature of my empirical setup to test model predictions of endogenous information acquisition theory.

²⁷The share price drift after a firm's earnings announcement is also widely known as post-earnings-announcement drift (PEAD).

²⁸Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) presents empirical evidence to show that both aggregate volatility and price of risk increase in recessions.

One distinguishing feature of the empirical setup is that private information of endogenously informed investors may well be incorporated into share price before earnings announcement. This “pre-earnings-announcement drift” can be captured by $CAR(-15, -1)$, the cumulative Fama-French 3-factor abnormal return in the pre-earnings-announcement period. When conducting additional analyses, I further decompose $CAR(-15, -1)$ into the sum of $CAR(-15, ecd)$ and $CAR(ecd + 1, -1)$, where “*ecd*” is the “earnings consensus date” of a firm’s end-of-quarter earnings. $CAR(-15, ecd)$ in effect captures the price responses to analyst earnings forecasts while $CAR(ecd + 1, -1)$ effectively captures the share price changes reflecting investors’ private information beyond what’s covered in analyst earnings forecasts. Figure 1.2 shows the timeline for the empirical settings in this chapter.

[Insert Figure 1.2 near here]

1.3.2. Model Predictions

Following prior literature in earnings surprises and informational efficiency, immediate and delayed price responses, $CAR(0, 1)$ and $CAR(2, 15)$, are the baseline measures for informational efficiency of individual firms around their quarterly earnings announcements. As discussed into detail later, the second component of PreEAD, $CAR(ecd + 1, -1)$, is recommended as another indicator of how much private information investors have about the to-be-announced firm earnings.

Prediction 1.1. Immediate price responses are more sensitive to earnings surprises if there are contemporaneous releases of macroeconomic announcements. This complementary effect on firm’s informational efficiency is larger during expansions than recessions.

Prediction 1.2. Delayed price responses are less sensitive to earnings surprises if there are contemporaneous releases of macroeconomic announcements. This complementary effect on firm’s informational efficiency is larger during expansions than recessions.

Predictions 1.1 and 1.2 are derived from Proposition 1.1. Upon receiving a free signal with precision K_{MA} about the aggregate risk, investor j will optimally re-allocate some of her learning capacity from the aggregate risk to firm-specific risks. Since this re-allocation pattern holds for all investors, then the average learning capacity allocated to individual firms will weakly rise. This re-allocation of learning capacity to individual firms are reflected by the enhanced informational efficiency of individual firms: larger immediate price responses and smaller delayed price responses for a given level of earnings surprises. Further analyses using observations in the subsamples of expansions and recessions, respectively, can confirm model predictions regarding the relative strength for the complementary effects of macroeconomic announcements on information efficiency of individual firms.

Prediction 1.3. The *Investor Private Information* (*InvestorPI*) component of pre-earnings-announcement drift is more sensitive to earnings surprises during expansions than recessions.

This prediction is derived to reflect the fundamental idea in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) that investors focus more on the aggregate risk in recessions and more on firm-specific risks in expansions. This is because recessions are times when the aggregate volatility is high and it is conventionally more valuable to learn about the more uncertain outcome. They provide empirical evidence at the mutual-fund level and argue that mutual fund managers have better stock-picking ability in expansions and better market-timing ability in recessions.

Prediction 1.3 emphasizes the time-varying feature for informational efficiency of individual firms by linking $\bar{K}_i$, the average learning capacity allocated to firm i , with its empirical counterpart. Firm-level predictions are achieved by aggregating all individual investors holding a firm. The *InvestorPI* component of pre-earnings-announcement drift serves as a proxy for how much learning capacity investors on average have allocated to a firm.

Prediction 1.4. The distracting effect of macroeconomic announcements on the *InvestorPI* component of pre-earnings-announcement drift is more pronounced during expansions than recessions.

Without conducting subsample analyses, alternative stories may seem sound when discussing the complementary effects of macroeconomic announcements on immediate and delayed price responses. However, Prediction 1.4 is potentially able to distinguish the endogenous informational efficiency framework in my work from competing stories.²⁹ This prediction is derived from Proposition 1.2 where disruptive increases in aggregate volatility before macroeconomic announcements are justified by the motivating evidence in Table 1.1 and Figure 1.1. Prediction 1.4 directly speaks to the attention re-allocation mechanism I propose in this chapter, and facilitates empirical examinations on how the attention re-allocation from firm-specific risks to the aggregate risk influence measures of firm informational efficiency.

1.4. Empirical Evidence

1.4.1. Data Sources and Variable Construction

Data of daily stock returns and other relevant variables are from CRSP. Data of earnings forecast consensus are from I/B/E/S. Release dates and types of macroeconomic announcements are downloaded from Bloomberg. Daily pricing factors to calculate cumulative abnormal returns are downloaded from Kenneth French’s Data Library online. The main empirical results use the cumulative Fama-French 3-factor abnormal returns with the estimation window $[-300, -46]$ days relative to a firm’s earnings announcement. *CAR* variables generated via alternative models (Carhart 4-factor model, CAPM, Market model) and the

²⁹For example, Sheng (2019) argues that releases of macroeconomic announcements draw people’s attention to study more about all risks, both the aggregate risk and firm-specific risks. His story is about investment professionals allocating their fixed amount of time and effort between playing golf and acquiring information for investment decisions. He argues it is the decrease in the amount of time and effort allocated to playing golf on days with releases of macroeconomic announcements that enables investment professionals to spend more time and effort in digesting firm-earnings news. However, his argument is unable to differentiate what is supposed to happen during expansions from that during recessions.

raw return in excess of market return are all considered for robustness check.

Following the literature about standardized unexpected earnings, earnings surprises are generated as the difference between the announced earnings and earnings forecast consensus, then scaled by the share price in the previous quarter end. In addition, I keep consensus earnings forecasts that are formed in the window $[-15, -2]$ days with at least three analyst forecasts. This data filtration does not drive the results but can be very important to exploring the pricing dynamics around the earnings announcements because of ruling out stale information or earnings consensus formed with one or two analyst earnings forecasts.

Following Sheng (2019), I download the release dates of macroeconomic announcements covering 4 types of information: FOMC, Nonfarm Payroll, ISM PMI and Personal Consumption. *Macroday* is an indicator variable equal to one if there are macroeconomic announcements released on the same day with a firm's quarterly earnings announcement. In addition, I use the NBER recessions following Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Using shocks in industrial production to capture aggregate risk, they empirically confirm that aggregate volatility is higher during recessions than expansions.³⁰

SameDayEarnings is the total number of earnings announcements released on the same day with a firm's earnings announcement. *Friday* is an indicator variable equal to one if a firm's earnings news is announced on a Friday. *InstitutionalOwnership* is the percentage of a firm's shares held by 13f institutional investors. *AnalystCoverage* is the number of analyst earnings forecasts that are used to form the earnings consensus by I/B/E/S. *StaleConsensus* is the time gap between the date of forming earnings consensus and the date of a firm's earnings announcement. *Size* is the natural log of market capitalization at the previous quarter end. *Turnover* is trading volume scaled by number of shares outstanding at the previous quarter end. *Momentum_3* is the holding-period return in the previous quarter,

³⁰The authors further confirm that aggregate volatility rises more than firm-specific uncertainty during recessions.

and *Momentum_9* is the 9-month holding period return before the 3-month holding period of *Momentum_3*. Table A1.1 provides detailed variable definitions.

1.4.2. Summary Statistics

Table 1.2 presents quarterly firm-level summary statistics for variables included in the regressions with the full sample in Panel A, the subsample of expansions in Panel B, and the subsample of recessions in Panel C. All *CAR* variables are in the unit of percentage points. Distributions of covariates are very similar across the three panels. One interesting feature is that one main outcome variable, $CAR(0, 1)$, the immediate price response, exhibits a higher dispersion during recessions than expansions. By focusing on the 75th and 25th percentiles of $CAR(0, 1)$, we can see the differential of the expansions subsample is 7.83 percentage points while that of the recessions subsample is 10.52 percentage points. The alternative measure of immediate price response, $CAR(-1, 1)$, exhibits a similar pattern.

[Insert Table 1.2 near here]

Figure 1.3 further confirms this heterogeneity in the dispersion of immediate price responses. The vertical axis is $CAR(-15, t)$, the horizontal axis is relative time to a firm's earnings announcement $t = 0$. To capture the cross-sectional dispersion, I calculate the difference in median $CAR(-15, t)$ between $SUE=11$ and $SUE=1$ in Panel A, $SUE=10$ and $SUE=2$ in Panel B, between $SUE=9$ and $SUE=3$ in Panel C. From these panels, we can see that immediate price responses $CAR(0, 1)$, or $CAR(-1, 1)$, exhibit a larger dispersion during recessions than expansions. These graphical results are consistent with the summary statistics.³¹

[Insert Figure 1.3 near here]

³¹Figure A1.2 further confirms this feature for each earning surprise quantile.

1.4.3. Main Results

Model Specification

Following Hirshleifer, Lim and Teoh (2009), and Dellavigna and Pollet (2009), I employ the following specification for empirical tests

$$\begin{aligned} CAR(t_1, t_2) = & \phi_0 + \phi_1 SUE_{i,t} + \phi_2 SUE_{i,t} * Macroday_t + \phi_3 Macroday_t \\ & + \Phi'_4 X_{i,t} + \Phi'_5 SUE_{i,t} * X_{i,t} + \epsilon_{i,t} \end{aligned}$$

where t_1 and t_2 are time points relative to the earnings announcement of firm i , and $X_{i,t}$ is the vector of covariates. The main coefficient of interest is ϕ_2 , indicating whether there exists a differential in the sensitivity of $CAR(t_1, t_2)$ to SUE between days with or without macroeconomic announcements. In similar settings, Hirshleifer, Lim and Teoh (2009) and DellaVigna and Pollet (2009) take the ratio of ϕ_2 over ϕ_1 to assess the economic significance of the sensitivity differential.

[Insert Table 1.3 near here]

Immediate Price Responses

The first two columns in Table 1.3 confirm the complementary effects of macroeconomic announcements on informational efficiency of individual firms regarding immediate price responses. Column (1) uses robust standard errors and includes no fixed effects, while column (2) further includes time- and firm-fixed effects. From the coefficient of the interaction term, $SUE * Macroday$, one can argue that immediate price responses are more sensitive to firm-earnings news when there are releases of macroeconomic announcements on the same day. This coefficient is not only statistically significantly different from zero but economically sizable as well. Taking the ratio of this coefficient over the coefficient on SUE gives us an 8.69% differential between the sensitivity of immediate price responses to SUE with and

without contemporaneous releases of macroeconomic announcements.

Columns (3) and (4) show that the complementary effects of macroeconomic announcements on informational efficiency of individual firms are statistically significant during expansions. I find no statistical significance for such effects during recessions. These results indicate that the complementary effects of macroeconomic announcements work through the attention re-allocation mechanism, and confirms that this attention reallocation effect is more pronounced during expansions than recessions.³²

The coefficients of the interaction terms, $SUE*SameDayEarnings$ and $SUE*Friday$, in columns (1) and (2) of Table 1.3 are consistent with the empirical evidence in Hirshleifer, Lim and Teoh (2009) and Dellavignall and Pollet (2009). Using subsamples of expansions and recessions, respectively, columns (3) and (4) suggest that the distracting effects of other firms' same-day earnings announcements and of Friday are statistically significant during expansions but insignificant during recessions. These results are consistent with the attention allocation pattern along the business cycle as argued in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). In particular, during recessions, the marginal value of acquiring more precise information about the aggregate risk is extremely high such that there is little learning capacity allocated to firm-specific risks. When little learning capacity is allocated to firm-specific risks, the distracting effects of other firms' same-day earnings announcements and of Friday are understandably insignificant.

Delayed Price Responses

Table 1.4 presents empirical evidence regarding the delayed price responses to earnings surprises. Again, the first two columns confirm the complementary effects of macroeconomic announcements on informational efficiency of individual firms but in terms of smaller delayed

³²One interesting feature in the subsample analyses is that immediate price responses are more sensitive to earnings surprises during recessions than expansions. This seemingly puzzling feature will be further discussed in the framework of endogenous information acquisition before a firm's earnings announcement.

price responses. Standard errors and fixed effects are similarly dealt with as in Table 1.3. From the coefficient of the interaction term $SUE*Macroday$, we can see that delayed price responses are *less* sensitive to firm-earnings news when there are releases of macroeconomic announcements on the same day. Taking the ratio of coefficients for $SUE*Macroday$ and SUE gives 73.92%, indicating that delayed price responses are substantially lower when firm earnings are announced with contemporaneous releases of macroeconomic news.

[Insert Table 1.4 near here]

Columns (3) and (4) in Table 1.4 further confirm model predictions that the attention re-allocation effects are more pronounced during expansions than recessions. The coefficient of the interaction term $SUE*Macroday$ is negative and statistically significant at the 1% level in the subsample of expansions while statistically insignificantly different from zero in the subsample of recessions. That is, in the subsample of expansions, Tables 1.3 and 1.4 present smaller delayed price responses and larger immediate price responses and jointly confirm that markets of individual firms' shares are more informationally efficient when there are contemporaneous releases of macroeconomic announcements. However, these complementary effects of macroeconomic announcements are absent in the subsample of recessions.

1.4.4. *Scaled Price Responses to Earnings Surprises*

One subtle feature of the results in Table 1.3 on the coefficient of SUE indicates that immediate price responses are more sensitive to earnings surprises during recessions than expansions. This pattern holds for observations either with or without pre-scheduled same-day macroeconomic announcements. This may appear contradictory with the idea that investors allocate more learning capacity to firm-specific risks during expansion than recessions.

Recall the summary statistics in Table 1.2: Immediate price responses exhibit a larger dispersion during recessions than expansions. Figure 1.3 confirms the larger dispersion dur-

ing recessions. Since SUE are cross-sectional 11 quantiles, a larger dispersion in immediate price responses means a steeper slope of immediate price responses along the earnings surprises quantiles. One way to make coefficients from these two subsamples comparable is standardization: Subtracting the subsample mean from $CAR(0, 1)$ and then divided by the subsample standard deviation for expansions and recessions, respectively. The resulting outcome variable is *Scaled* $CAR(0, 1)$.

Table 1.5 presents the results using scaled immediate and delayed price responses as the outcome variables. Regarding *Scaled* $CAR(2, 15)$, the coefficients on SUE in columns (3) and (4) maintain a similar relative magnitude with those in Table 1.4, suggesting more informationally efficient markets in expansions. However, the baseline sensitivity of immediate price responses to earnings surprises during expansions, 0.112, is still marginally lower than that during recessions, 0.117. These coefficients measure, on days without macroeconomic announcements, how sensitively the scaled immediate price responses react to earnings surprises, taking into account that the “unscaled” immediate prices responses in the subsample of recessions have a larger dispersion. That is, the scaled results are still far from the conjecture that immediate price responses should be more sensitive to earnings surprises during expansions because investors on average have more precise firm-specific information during expansions.

[Insert Table 1.5 near here]

One might wonder whether immediate and delayed price responses are able to tell the whole story when analysing informational efficiency of individual firms from an information acquisition perspective. In particular, investors face the endogenous choice of attention allocation not only upon the releases of macroeconomic announcements but also before these pre-scheduled releases. Investors who are endogenously well-informed about a firm may want to trade before its end-of-quarter earnings announcement. Their private information about

this firm will be incorporated into its share price via trading. Therefore, a firm with extremely well-informed investors may experience a very small price jump upon its announcement of a positive earnings surprise because much of this positive earnings surprise has already been reflected in firm share price before the end-of-quarter earnings is announced.

Following this line of reasoning, one straightforward question arises: Shouldn't we further explore share price trends in the "pre-earnings-announcement" period before ignoring the possibility that private information about the end-of-quarter earnings has been incorporated into share price? What if firms to which investors on average have allocated more learning capacity experience share price trends in the pre-earnings announcement period in the same direction with the earnings news to be announced? Regressing measures of investor private information in the pre-earnings-announcement period onto SUE can suggest to what extent share price trends due to investor private information are explained by the to-be-announced earnings news. This question leads to the next part of the empirical section substantially focusing on investors' endogenous information acquisition behavior prior to earnings announcements.

1.4.5. Endogenous Information Acquisition Prior to Earnings Announcements

Pre-Earnings-Announcement Drifts (PreEADs)

$CAR(-15, -1)$ measures share price drift before earnings announcements. The coefficients of regressing PreEADs onto SUE indicate whether and to what extent PreEADs can be explained by the to-be-announced earnings surprises. Column (1) in Table 6 shows that pre-scheduled releases of macroeconomic news have distracting effects on investors of individual firms in the pre-earnings-announcement window. Subsample analyses in columns (2) and (3) further show that such distracting effects are statistically significant during expansions but not during recessions.

Notably, during the whole pre-earnings-announcement period, equity analysts may issue earnings forecasts. Equity analysts can substantially cover almost all relevant information in the public domain (Kacperczyk and Seru (2007)). Nonetheless, I have theoretically explored investors' behavior of acquiring private information about individual firms. That is, I need to deal with the fact that $CAR(-15, -1)$ almost surely contains the price impacts of analyst earnings forecasts. Thus, additional analyses are in need to decompose $CAR(-15, -1)$ and figure out the component that can capture investors' private information about the to-be-announced earnings news.

Investor Private Information

One conjecture can be that informed trading prior to earnings announcements is likely to drive stock prices towards the same direction of earnings surprises. One extreme situation could be that investors of a firm are nearly perfectly informed about the to-be-announced earnings surprises such that there is little immediate price response upon earnings announcement. This section empirically explores the pre-earnings-announcement drift and its two components: Response to analyst earnings forecast consensus (REF) and investor private information (InvestorPI).

[Insert Table 1.6 near here]

Focusing on the coefficient of SUE , Table 1.6 broadly confirms that investors, during recessions, do not acquire private information about individual firms but simply follow analyst earnings forecasts. I find that pre-earnings-announcement drift do capture information contained in earnings news to be announced. From the expansions subsample analyses in columns (2), (5) and (8), we can see that both analyst earnings forecasts and investor private information will drive stock price towards the direction of earnings surprises to be announced. This is reflected in the sum of coefficients for SUE in columns (5) and (8), 0.180 and 0.111, being roughly equal to 0.292, the coefficient for SUE in column (2).

However, using the subsample of recessions, I find that only analyst earnings forecasts will drive stock price towards the direction of earnings surprises to be announced. Earnings surprises have no explanatory power over cumulative abnormal return due to investor private information. This indicates that, in recessions, investors acquire very little private information about the to-be-announced earnings news but simply follow analyst earnings forecasts. This result is consistent with Loh and Stulz (2018) where the authors provide empirical evidence to argue that investors, in recessions, rely more on analyst recommendations and earnings forecast revisions.

These differential patterns regarding the coefficient of SUE between the expansions and recessions subsamples speak to the puzzling results in Tables 1.3 and 1.5. During expansions, investors acquire private information about to-be-announced earnings news and such private information has been substantially incorporated into share price before earnings announcements. In consequence, immediate price responses are actually smaller during expansions, regardless of contemporaneous macroeconomic announcements. During recessions, however, investors tend to simply follow analyst reports and do not acquire private information prior to earnings announcements. Upon observing earnings surprises, investor responses can result in larger immediate price responses.

Distracting Roles of Macroeconomic Announcements

Focusing on the coefficient of the interaction term, $SUE*Macroday$, Table 1.6 shows that pre-scheduled releases of macroeconomic news have distracting effects on investors' behavior of acquiring private information about individual firms. Specifically, the negative and statistically significant coefficient of $SUE*Macroday$ in column (7) suggests that investors tend to acquire less private information about the to-be-announced earnings news accompanied with pre-scheduled contemporaneous macroeconomic announcements (than without). When conducting subsample analyses, I find that such distracting effects persist only in expansions.

This is consistent with the model in the “low- λ_N ” regime: Investors re-allocate substantial learning capacity from firm-specific risks to the aggregate risk.

In the subsample of recessions, nonetheless, I find no such statistical significance. This is consistent with the model in the “high- λ_N ” regime that suggests no significant re-allocation of learning capacity from firm-specific risks to the aggregate risk. Overall, these results strongly support model predictions regarding the differentially distracting effects of pre-scheduled releases of macroeconomic news on investors’ behavior of acquiring private information about individual firms. Furthermore, these differential effects distinguish my attention re-allocation mechanism from competing stories.

1.5. Robustness and Validation Checks

1.5.1. Regulation Fair Disclosure

One may be concerned about the practice of selective disclosure that used to be conducted by many firms before the Regulation Fair Disclosure (or Reg FD) adopted in 2000. Reg FD was designed to effectively remove the superior access to “material non-public” information from firm management enjoyed by certain industry professionals and selected shareholders.³³ Table 1.7 replicates the main results exclusively using the observations in the post-Reg FD regime. Essentially, the sample in this table is from 2001 to 2017, intentionally removing all observations in the pre-Reg FD regime. Without being compounded by the implementation effects, this table excludes all observations in 2000. We can see that all results are robust in the post-Reg FD regime.

[Insert Table 1.7 near here]

³³Koch, Lefanowicz and Robinson (2013) and Leuz and Wysocki (2016) summarize the empirical evidence regarding the effects of Reg FD on the informational environment of individual firms.

1.5.2. *Illegal Insider Trades*

One may be concerned about illegal insider trades, especially those specifically associated with insiders illegally using earnings-related information for trading.³⁴ There seems no perfect way to deal with the possibility of a firm being illegally traded. However, one possible way to mitigate such concerns is to remove firms that have ever been involved with illegal insider trades prosecuted by the SEC. Table 1.8 replicates all the main results by excluding observations of firms ever involved with illegal insider trades. We can see that all results are robust to this refined sample.

[Insert Table 1.8 near here]

1.5.3. *Post I/B/E/S Consensus*

One may also be concerned about the fact that some analyst earnings forecasts are issued after a firm's earnings consensus is formed by I/B/E/S. This may threaten the validity of decomposing $CAR(-15, -1)$ into the sum of REF and $InvestorPI$ and capturing share price responses to analyst earnings forecasts and investor private information, respectively. Possibly, the price trend after the earnings-consensus-formation date not only reflects investors' private information but follows the newly issued earnings forecasts as well. To mitigate this concern, Table 1.9 replicates the main results exclusively using the observations without after-consensus analyst earnings forecasts. We can see that all results are robust to removing the observations with after-consensus analyst earnings forecasts.

[Insert Table 1.9 near here]

³⁴Kacperczyk and Pagnotta (RFS forthcoming) collect comprehensive information of illegal insider trades from SEC legal case files, of which around 10% are about earnings announcements.

1.5.4. *Trading Volume upon Earnings News*

The attention re-allocation mechanism I propose suggests that, upon macroeconomic announcements being released, investors temporarily allocate more attention to digest firm-specific information. This framework indicates that trading volume upon firm-earnings news is supposed to be higher on *Macroday*.³⁵ Following Hershleifer, Lim and Teoh (2009), I generate abnormal trading volume as the difference between the natural log of daily trading volume and the averaged natural log of daily trading volume in the recent past.³⁶

Figure 1.4 presents this idea. Since absolute earnings surprises are an important factor of trading volume, I generate quintiles of absolute earnings surprises. Figure 1.4 presents the trading volume comparisons around firm-earnings news announced on *Macroday* and *NonMacroday* for observations with the 3rd absolute earnings surprise quintile.³⁷ For similar levels of absolute earnings surprises, firms whose earnings news are announced on *Macroday* tend to experience higher trading volume than those whose earnings news are announced on *NonMacroday*. These are consistent with the attention re-allocation mechanism.

[Insert Figure 1.4 near here]

1.5.5. *The Trailing Effects of Macroeconomic Announcements*

My theoretical framework indicates that macroeconomic announcements matter for informational efficiency of individual stocks through the mechanism of investors re-allocating their attention across the aggregate risk and firm-specific risks. To further check the validity of regressions results involving immediate and delayed prices responses and investor private

³⁵Hershleifer, Lim and Teoh (2009) and DellaVigna and Pollet (2009) both suggest that trading volume requires investor attention. They provide empirical evidence indicating that trading volume upon firm-earnings news tends to be lower when investors are more distracted.

³⁶Hershleifer, Lim and Teoh (2009) use the average of natural log of daily trading volume from day -41 to day -11.

³⁷Graphs for the other 4 quintiles of absolute earnings surprises can be found in Figure A1.3.

information, I follow Ben-Rephael, Da and Israelsen (2017) and download Bloomberg readership data that measure firm news reading and news searching activities by all Bloomberg terminal users at the daily frequency.

Figure A1.1 presents the timing relation between macroeconomic announcements and investor's activities of news reading and searching. The key message is that Bloomberg terminal users allocate more attention to news reading and searching activities upon the releases of macroeconomic announcements. This effect has some momentum pattern: Bloomberg terminal users tend to largely focusing on digesting firm-specific information in the next couple of days. One may interpret this pattern as the trailing effects of macroeconomic announcements; that is, the attention re-allocation effects of macroeconomic announcements can stay for about two to three days.

To further explore this trailing effect, I extend the definition of *Macroday* into several alternatives, namely, *MacrodayAlt*(0, 1), *MacrodayAlt*(0, 2), and *MacrodayAlt*(0, 3). *MacrodayAlt*(0, 1) is an indicator variable for days with macroeconomic announcements or days right after *Macroday* being released in the previous day. The latter two are similarly defined. Table A1.4 shows that the main results of Table 1.3 still hold in this setting. In particular, the magnitudes of coefficients for the interaction term $SUE * MacrodayAlt$ are smaller in the subsample of recessions than that of expansions.

1.5.6. Strategic Timing by Firm Management

Another concern is from a behavioral perspective: Firm managers may strategically time the pre-scheduled macroeconomic announcements regarding when to announce firm earnings. For example, one could argue that firm managers who are confident to beat analyst forecasts may want to announce firm quarterly earnings on *Macroday* because they believe doing so can let the markets fully react to their higher-than-forecast earnings. This could lead to share price quickly adjusting to higher levels. If this is true, we can expect earnings surprises to

be positively associated with *Macroday*. Table A1.12 presents the OLS regressions of *SUE* onto *Macroday* and covariates using the whole sample, the subsample of expansions, and the subsample of recessions, respectively. However, I find no statistical significance for this association, indicating that strategically timing *Macroday* by firm management is not a big concern in this framework.

1.5.7. *Alternative Timing of Macroday*

If the pre-scheduled macroeconomic announcements have distracting effects on private information acquisition by investors prior to being released, they must have such effects on firms whose earnings news are to be announced the next day. Tables A1.9 and A1.10 confirm this idea. Table A1.9 replicates the main results of InvestorPI but using alternative pricing models to calculate abnormal returns, and Table A1.10 further mitigates concerns regarding Reg FD, illegal insider trades, and analyst earnings forecasts issued after forming I/B/E/S consensus.

1.5.8. *Immediate Price Response with Refined Samples*

One may be concerned with the results of immediate price responses, $CAR(0, 1)$, covering a two-day period, because the effects of macroeconomic announcements on the next day of a firm's earnings news could be captured by $CAR(0, 1)$ as well. This is undesirable, though previous research faces similar issues. To address this issue, I exclude observations with macroeconomic announcements scheduled on the next day of a firm's earnings announcement. This practice refines the (sub)sample of observations for regressions, ensuring that no observations experience releases of macroeconomic information at time 1 (i.e. earnings announcement day is time 0). Tables A1.13 and A1.14 confirm that the results regarding immediate price responses are qualitatively identical and quantitatively similar to the main results in Table 1.3.

1.5.9. *Firm Earnings Announcements and Macroeconomic Announcements*

Another concern originates from one subtle assumption in model setup: Macro news, $\tilde{Z}_N$, is independent of firm- i -specific news, $\tilde{Z}_i$. In the empirical analyses, I exclusively focus on whether there are releases of macroeconomic information. Thus, one may wonder if macro news affects the immediate price response to firm-specific news. To address this issue, I use CRSP daily value-weighted market return as the proxy for macro news and focus on observations on Macroday. The rationale is straightforward: Better-than-expected releases of macroeconomic information can be captured by positive market returns at the daily frequency. The goal of this empirical exercise is to check if good or bad macro news may affect the way share prices respond to earnings surprises.³⁸ In Table A1.15, I find no statistical significance for the coefficient of the interaction term “SUE*MktRet”. This mitigates the concern that macro news and firm-specific news may interact such that the way share price respond to earnings surprise could be different depending on good or bad macro news.

1.6. *Summary of Chapter One*

Pre-scheduled releases of macroeconomic information can arguably have crucial effects on the informational environment of individual firms. There are two competing effects of macroeconomic announcements on informational efficiency of individual firms that are theoretically accommodated and empirically examined in this chapter. When investors digest firm-earnings news, contemporaneous releases of macroeconomic announcements can be distracting if they contain information about the aggregate risk that competes with firm-specific risks to occupy investors’ learning capacity. Pre-scheduled releases of macroeconomic announcements can be distracting during the pre-announcement window as well if aggregate volatility disruptively increases.

³⁸ “Good” macro news means “better-than-expected” release of macroeconomic information.

However, macroeconomic announcements reveal valuable information about the aggregate risk to the public domain such that investors can be less occupied, at least temporarily, in collecting such information by themselves. This enables investors to allocate more learning capacity to firm-specific information. That is, releases of macroeconomic information result in attention re-allocation from the aggregate risk to firm-specific risks. Therefore, macroeconomic announcements, upon being released, can have complementary effects on investors digesting firm-specific information.

Using the rational inattention framework in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) as a building block and combining both complementary and distracting views, this chapter proposes the attention re-allocation mechanism to understand the effects of macroeconomic announcements on informational efficiency of individual firms. Releases of macroeconomic information are intuitively modelled as all investors receiving an informative signal of the aggregate risk without exhausting their own resources. The model theoretically confirms that macroeconomic announcements have both complementary effects upon being released, and distracting effects prior to being released, on informational efficiency of individual firms.

More importantly, this model further predicts that such complementary and distracting effects are more pronounced during expansions than recessions. These predictions emphasize the time-varying feature of attention re-allocation between the aggregate risk and firm-specific risks due to pre-scheduled shocks to investors' information environment. This model offers new insights into the roles of macroeconomic announcements when investors are presumably acquiring private information on a daily basis about the aggregate risk and firm-specific risks. Overall, these predictions substantially distinguish my endogenous information acquisition framework from other competing stories.

Empirically, this chapter confirms the enhanced informational efficiency of individual firms whose quarterly earnings announcements are accompanied with same-day macroeconomic announcements. More importantly, I provide supportive evidence for core predictions regarding states of the business cycle. I find that such complementary effects are statistically significant only in the subsample of expansions while I find no statistical significance in the subsample of recessions. These empirical findings suggest the importance of using an endogenous information acquisition framework to understand the time-varying features of informational efficiency upon the release of firm-earnings news.

Finally, I provide supportive evidence for the distracting effects of pre-scheduled macroeconomic announcements on investors' private information acquisition activities during the pre-earnings-announcement period. I decompose the whole pre-earnings-announcement drift into two components: price response due to analyst earnings forecasts and price response due to investors' private information. I find that during expansions, investors not only follow analyst earnings forecasts but also acquire private information about the to-be-announced earnings news. I also find that pre-scheduled macroeconomic announcements have substantially distracting effects on investors' information acquisition behavior. However, during recessions, investors do not acquire such firm-specific private information but simply follow analyst earnings forecasts. I find no statistical significance for the distracting effects of macroeconomic announcements in the subsample of recessions, either.

All these empirical results are consistent with model predictions. More importantly, these results suggest that immediate and delayed price responses alone may not be able to tell the whole story when empirically examining the informational efficiency of individual firms. Instead, pre-earnings-announcement drift and its sub-components should be further explored to have a more complete picture regarding the effects of macroeconomic announcements. Future research may exploit high-frequency institutional investors' transaction data around firm-earnings news to examine their endogenous information acquisition in different states

of the business cycle.

2. Chapter Two

2.1. Related Literature and Contributions

This chapter provides a new layer of theoretical motives for investors to make costly monitoring effort. I introduce two underlying assumptions to formally distinguish between monitoring and information acquisition. First, I assume that institutional investors inevitably acquire firm-specific information during the process of monitoring a firm.³⁹ The more monitoring effort to make on a firm, the more precise this piece of firm-specific information. This piece of information is “non-separable” from monitoring in the sense that the precision of firm-specific information acquired during the process of monitoring a firm is a monotonically increasing function of monitoring effort on that firm.

Second, I assume that institutional investors can acquire firm-specific private information for trading purposes via conducting independent research, during which there are no activities of engaging with corporate executives or the board of directors.⁴⁰ This piece of information is “separable” from monitoring in the sense that the precision of firm-specific information acquired via conducting independent research is not an explicit function of monitoring effort. These two assumptions enable my work to reserve the flexibility that investors may optimally choose to devote all valuable resources to conducting independent research and leave no capacity for monitoring at all.

³⁹For example, institutional investors may acquire some “soft information” about CEO ability or internal operating conditions of a firm when proactively communicating and engaging with firm managers and board directors. Accessing such soft information requires monitoring effort.

⁴⁰Many active mutual funds do have their own “in-house” research department trying to create profitable stock-picking strategies by processing and analyzing firm-specific information. This is a separate source of obtaining private information.

These underlying assumptions have crucial implications for information acquisition. Both within-firm complementarity and cross-firm substitutability between monitoring and information acquisition are derived from the model. Specifically, I propose the “monitoring-for-learning” mechanism to describe that investors in my model *re-allocate* monitoring effort from firms with low value of information acquisition to those with high value of information acquisition. This monitoring-for-learning mechanism argues that, besides the motivation purely for enhancing fundamental values, investors optimally choose to make additional effort to monitor firms whose marginal value of more precise information is high, because they rationally anticipate the beneficial effects of monitoring on information acquisition (and ultimately on portfolio choices). Similarly, investors optimally choose to make less effort to monitor firms whose marginal value of more precise information is low, because they rationally anticipate the beneficial effects of the saved capacity being *re-allocated* to firms with high marginal value of more precise information. This re-allocation pattern essentially links information acquisition choices with determinants of monitoring effort.

Another contribution of my work is to enrich the set of feasible empirical tests for information acquisition theory.⁴¹ This chapter first explores the joint cross-sectional patterns of monitoring and information acquisition, and then forms predictions regarding the relation between information acquisition and determinants of monitoring effort. Put differently, my model suggests that an institutional investor may not be equally informed about all firms within her portfolio. Instead, she optimally chooses to have more precise information about certain firms than the other firms within her portfolio, depending on engagement effectiveness and initial holdings. That is, institutional investors tend to acquire more precise information about the firms they can more effectively engage with and about those they have larger initial holdings in. These “within-portfolio” predictions are supported by empirical evidence where measures of stock-picking ability serve as proxy for precision of acquired private infor-

⁴¹Veldkamp (2011, pp.146-147) highlights lack of observability and empirical testability as the potential problems with theoretical models of information acquisition, because empirical tests require observables are regressed on observables. This book also summarizes established ways to measure information flows.

mation. I find that institutional investors have differentially higher scores of stock-picking ability among subgroups of firms as predicted.

In addition, my model suggests that, among all institutional investors of a firm, investors with high initial holdings have more precise information about this firm than investors with low initial holdings. This is a “within-firm” prediction regarding all investors of a given firm. Empirically, I find that the investor subgroup with high initial holdings tend to have a higher score of stock-picking ability than the subgroup with low initial holdings. To mitigate concerns of some shareholders having privileged access to material non-public information due to their substantial holdings in a firm, I use Regulation Fair Disclosure (or “Reg FD”) introduced in 2000 as an exogenous shock to the information environment of US stock markets, and compare the patterns of stock-picking ability along the dimension of percentage holdings in a firm in the both Pre-2000 and Post-2000 regimes.

Using 5-year subsamples before and after 2000, exclusive, I find that stock-picking ability is, in general, increasing in percentage holdings in both regimes, consistent with model predictions. However, the importance of percentage holdings to stock-picking ability decreases dramatically from the Pre-2000 to the Post-2000 regimes. This is consistent with the intention of introducing Reg FD to remove privileged access to material non-public information via substantial holdings in a firm.

This chapter broadly relates to the literature on endogenous information acquisition (Grossman and Stiglitz (1980), and Verrecchia (1982)).⁴² Recent theoretical work on endogenous information acquisition introduces the framework of “rational inattention”, or the constraint

⁴²Grossman and Stiglitz (1980) build a competitive equilibrium framework where a continuum of investors choose to either pay a fixed information cost and get informed or not pay and stay uninformed. Their model implicitly assumes a common single signal available to all at a homogeneous cost. Verrecchia (1982) further allows investors to endogenously choose the precision level of private information and explores the relation between the informativeness of the pricing system and the cost of acquiring information. His framework assumes informed traders independently observe “diverse signals”, each signal containing the true value plus a cross-sectionally uncorrelated error term.

of limited learning capacity, to study optimal attention allocation across multiple risky assets or risk factors.⁴³ Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) provide a theoretical framework of attention allocation for mutual fund managers and present supportive empirical evidence using business-cycle variations in aggregate volatility and risk aversion. Compared to this line of research, my work undertakes a “within-portfolio” approach and focuses on how investors optimally allocate valuable resources in both monitoring and information acquisition among the firms within their portfolios. My work indicates that investors have differentials of stock-picking ability among subgroups of firms within their portfolios.

The rest of this chapter proceeds as follows. Section 2.2 introduces the model setup. Section 2.3 solves the model. Section 2.4 checks alternative ways to set up the model for robustness. Section 2.5 derives empirically testable predictions from the model. Section 2.6 briefly describes relevant data, Section 2.7 constructs the empirical measure of stock picking ability, the key dependent variable for regressions, and Section 2.8 summarizes this chapter.

2.2. *Model Setup*

There are N firms. The fundamental value of firm i is $\tilde{V}_i$, defined as the sum of its expected payoff $\bar{V}_i$ and a firm-specific random component $\tilde{z}_i$; that is,

$$\tilde{V}_i = \bar{V}_i + \tilde{z}_i \tag{16}$$

where $\tilde{z}_i$ has zero mean with variance σ_i for $i = 1, \dots, N$. For simplicity and tractability, the firm-specific random component is assumed to be cross-sectionally independent.⁴⁴ Assume

⁴³Institutional investors have their own research capacity or networks to gather non-public information. An upper-bounded capacity of their research capacity requires optimally allocating such valuable resources. Van Nieuwerburgh and Veldkamp (2009) address how endogenously acquired information enlarges informational asymmetry between home and foreign investors. Van Nieuwerburgh and Veldkamp (2010) focus on how investors with limited information processing capacity optimally allocate their attention across multiple risky assets.

⁴⁴Eigen-value decomposition may be applied to deal with cross-sectionally correlated error terms. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) provide further detail regarding applying eigen-value decomposition to cross-sectional correlation.

there is a continuum of CARA investors with mass one and absolute risk aversion ρ .⁴⁵ Investor $j \in [0, 1]$ is endowed with a fraction $\beta_{ij} \geq 0$ of firm i , and $\int_0^1 \beta_{ij} dj = 1$.

[Insert Figure 2.1 near here]

Penal A of Figure 2.1 shows the model timeline. In this static model, each investor j faces a multi-stage problem with endogenous choices of monitoring effort, independent research, and portfolio choices in stages 1 to 3, respectively. In stage 1, investor j decides which firm to monitor and how much monitoring effort to make. Let $m_{ij} \geq 0$ denote the monitoring effort allocated to firm i by investor j . Initial wealth after monitoring is $\sum_{i=1}^N (\beta_{ij} \bar{V}_i - m_{ij})$. In stage 2, based on the choice of monitoring effort m_{ij} , investor j chooses how much independent research to conduct about firm i and further reduces her uncertainty about $\tilde{V}_i$. In stage 3, investor j makes an optimal portfolio choice given her monitoring effort and information acquisition decisions in the first two stages.

Penal B of Figure 2.1 presents a graphical description to show the effects of monitoring and information acquisition under the two underlying assumptions. Investors can choose to acquire information from two non-overlapping pools of information: Pool I and Pool II. The first underlying assumption states that, during the process of monitoring a firm, investors inevitably acquire firm-specific information from Pool I. There are two effects of monitoring a firm: enhancing its expected payoff and reducing posterior uncertainty at the same time. That is, the firm-specific information acquired when monitoring a firm reduces investors' posterior uncertainty about this firm. The more monitoring effort to make on a firm, the more precise this piece of firm-specific information.

⁴⁵One reason why CARA preference is commonly used in rational expectations models is that there is no wealth effect and thus concerns about heterogeneous initial wealth are largely mitigated. Liu, Peleg, and Subrahmanyam (2010) build up a continuous-time framework with a CRRA agent who jointly solves the problem of portfolio choice and information acquisition. Here in the setup is not a model for blockholders but with a continuum of investors. Figure A3.1 indicates a diverse pool of institutional shareholders among the largest 500 firms in the US.

The second underlying assumption states that, without activities of engaging with corporate executives or the board of directors, investors can acquire firm-specific information for portfolio-choice purposes from Pool II via conducting independent research. The precision of this information is not an explicit function of monitoring effort. Acquiring information via conducting independent research reduces investors' posterior uncertainty. The second assumption emphasizes that acquiring firm-specific information via conducting independent research is a separate information source from acquiring firm-specific information via making monitoring effort.

Specifically, in line with the literature of institutional ownership and corporate governance suggesting that institutional monitoring pressure enhances firm performance, the fundamental value of firm i can be constructed as

$$\bar{V}_i = \phi_i \int_0^1 \ln(1 + m_{ij}) dj \quad (17)$$

where ϕ_i measures how effectively investors can engage with firm i 's managers to improve its fundamental value via external governance.⁴⁶ Equation (17) can be considered as a variant of production function with monitoring effort being the input and firm fundamental value the output.

The role of acquiring private information is to reduce the prior uncertainty of firm i , σ_i , down to the posterior uncertainty of firm i , $\bar{\sigma}_i$. All investors are assumed to observe $\bar{V}_i$ before stage 2 starts. Investor j has an information processing capacity K_j to be allocated to N firms. The more of this information processing capacity allocated to firm i , the more precise the acquired information about $\tilde{z}_i$ in stage 2. I use IR_{ij} to denote the precision of

⁴⁶Edmans and Manso (2011) use a similar natural-log functional form to express how investor monitoring effort can help enhance firm expected payoffs, and they interpret the coefficient multiplied with the natural log of 1 plus effort as the “productivity” of effort. One subtle assumption embedded in this functional form is the level of monitoring pressure is usually low such that marginally higher levels of monitoring pressure will not cause adverse effects on firm fundamentals. ϕ_i here in (2) allows the productivity of monitoring effort to be heterogeneous across firms.

firm- i information acquired by investor j via independent research in stage 2. Noisy rational expectations models normally assume the private signal is still a noisy signal of $\tilde{V}_i$ taking the form:

$$\tilde{\theta}_{ij} = \tilde{V}_i + \epsilon_{ij}^{\theta} \quad (18)$$

where $\epsilon_{ij}^{\theta} \sim N\left(0, \frac{1}{IR_{ij}}\right)$, or put differently, $\tilde{\theta}_{ij}|\tilde{V}_i \sim N\left(\tilde{V}_i, \frac{1}{IR_{ij}}\right)$.⁴⁷ That is, IR_{ij} measures how precise investor j 's private information about firm i acquired via independent research.

The first underlying assumption requires investor j to inevitably acquire a piece of private information when monitoring the firm in stage 1. This piece of private information is a private signal about $\tilde{V}_i$ and takes the form of $\tilde{\nu}_{ij} = \tilde{V}_i + \epsilon_{ij}^{\nu}$ with $\tilde{\nu}_{ij}|\tilde{V}_i \sim N\left(\tilde{V}_i, \frac{1}{\kappa(m_{ij})}\right)$, where $\kappa'(m_{ij}) > 0$ and $\kappa''(m_{ij}) < 0$. Here $\kappa(m_{ij})$ measures the precision of firm-specific private information acquired during the process of investor j monitoring firm i . This inevitably acquired information due to monitoring firm i in stage 1 is, in nature, conditionally orthogonal to information $\tilde{\theta}_{ij}$ acquired via independent research in stage 2. For simplicity, a functional form has been assumed: $\kappa(m_{ij}) = \phi_m \ln(1 + m_{ij})$, where $\phi_m > 0$ transforms (the log of) monitoring effort into precision of firm-specific information.

Taking into account the information acquired by investor j during the process of monitoring firm i in stage 1, total information acquired by investor j about firm i takes the form: $K_{ij} = \kappa(m_{ij}) + IR_{ij}$. One thing to be clear is that there is no “free-lunch”: The information acquired during the process of monitoring also occupies investor j 's learning capacity. Thus, in this model, the constraint of learning capacity takes the following form:

$$\sum_{i=1}^N K_{ij} \leq K_j \quad (19)$$

⁴⁷ ϵ_{ij}^{θ} 's are assumed to be cross-sectionally independent.

where $K_{ij} = \kappa(m_{ij}) + IR_{ij}$. The “no-forgetting” constraint in the presence of monitoring effort takes the form:

$$K_{ij} \geq \kappa(m_{ij}) \quad (20)$$

for $i = 1, \dots, N$.⁴⁸ Equivalently, (20) requires non-negativity of IR_{ij} ; that is, the precision of information acquired via conducting independent research is non-negative.

2.3. Backward Induction

Investor j faces a three-stage problem that can be solved using backward induction. In stage 3, investor j makes her portfolio choice by choosing the quantities of firm shares to hold, denoted by the vector $q_j = (q_{1j}, \dots, q_{Nj})'$. The vector of firm payoffs is $\tilde{f} = (\tilde{V}_1, \dots, \tilde{V}_N)'$ and the vector of share prices is $\tilde{p} = (p_1, \dots, p_N)'$. Let W_j denote investor j 's terminal wealth, which takes the form:

$$W_j = rW_0 + q_j'(\tilde{f} - \tilde{p}r) \quad (21)$$

where r is the gross riskfree rate. In this stage, investor j choose q_j to maximize stage-3 expected utility U_{3j} :

$$U_{3j} = E_j(W_j) - \frac{\rho}{2} Var_j(W_j) \quad (22)$$

where $E_j(W_j)$ and $Var_j(W_j)$ are the conditional expectation and variance conditioning on investor j 's information sources. Maximizing (22) subject to (21) delivers the demand for

⁴⁸The no-forgetting constraint in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) requires $K_{ij} \geq 0$.

firm i from investor j :

$$q_{ij} = \frac{E_j \left(\tilde{V}_i \right) - r p_i}{\rho \text{Var}_j \left(\tilde{V}_i \right)} \quad (23)$$

Equilibrium prices are determined by equating supply and demand of firm shares. In this model, the number of shares outstanding of each firm is set to be one such that quantities traded or held are actually the fractions of firms that are traded or held. As assumed in standard noisy rational expectations models, noise traders (or liquidity traders) submit random orders denoted by the vector $x = (x_1, \dots, x_N)'$, where x_i has zero mean with variance σ_x and x_i 's are cross-sectionally uncorrelated. Therefore, the market clearing condition takes the form:

$$\int_0^1 q_j dj = \mathbf{1} + x \quad (24)$$

To simplify notations, define $\alpha_i = \frac{1}{\sigma_i}$ for $i = 1, \dots, N$ and $\gamma = \frac{1}{\sigma_x}$.

Lemma 2.1. The equilibrium price of firm $i = 1, \dots, N$ takes the form:

$$p_i^* = \frac{1}{r} \left(\frac{\alpha_i \bar{V}_i + \left(\bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma \right) \tilde{V}_i - \left(\frac{\bar{K}_i}{\rho} \gamma + \rho \right) (1 + x_i)}{\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma} \right) \quad (25)$$

where $\bar{K}_i = \int_0^1 K_{ij} dj$ is the average attention allocated to firm i across all investors $j \in [0, 1]$. Consistent with Admati (1985), p_i^* is first conjectured and then verified to be a linear function of $\bar{V}_i$, $\tilde{V}_i$, and supply shock x_i .⁴⁹ Derivations of all lemmas and propositions in this chapter can be found in Appendix B.

⁴⁹This chapter focuses on the linear-price equilibrium of rational expectations models.

Given the optimal portfolio choice in stage 3, investor j faces the following optimization problem when choosing signal precision K_{ij} :

$$\max_{K_{ij}} \sum_{i=1}^N \lambda_i K_{ij} + \text{constant} \quad (26)$$

subject to the constraints (19) and (20), where

$$\lambda_i = \bar{\sigma}_i \left[1 + (\rho^2 \sigma_x + \bar{K}_i) \bar{\sigma}_i \right] + \rho^2 \bar{\sigma}_i^2 \quad (27)$$

and $\bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2 \sigma_x}$ is the average posterior precision about firm i .⁵⁰ The coefficient λ_i measures the marginal value of acquiring more precise information about firm i and applies to all investors of firm i . Let K_{ij}^* denote the optimal choice of K_{ij} given her monitoring effort allocation $m_{1j}, \dots, m_{Nj}$.

Lemma 2.2. For each investor $j \in [0, 1]$, $\frac{\partial K_{ij}^*}{\partial m_{ij}} \geq 0$, and $\frac{\partial K_{ij}^*}{\partial m_{kj}} \leq 0$ when $i \neq k$.

This lemma says that there is complementarity between monitoring and information acquisition decisions within the same firm and substitutability across firms. The within-firm complementarity suggests that, given an exogenous increase in monitoring effort on firm i and everything else being equal, the total amount of private information about firm i acquired by investor j is higher. The feature that both IR_{ij} and $\kappa(m_{kj})$ take up investor j 's valuable resources gives rise to the cross-firm substitutability of information acquisition about firm i and monitoring on firm k , $i \neq k$. The cross-firm substitutability suggests that, given an exogenous increase in monitoring effort on firm k and everything else being equal, more of investor j 's capacity is captured by $\kappa(m_{kj})$, crowding out information acquisition about other firms from her capacity constraint.

⁵⁰One big contribution of Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) is to transform $U_{3j}(q_j(\tilde{p}^*))$ into a linear function of K_{ij} 's.

Next, we need to solve for the optimal allocation of monitoring effort across firms. Given the optimal information acquisition decisions $K_{ij}^*(m_{ij})$ for $i = 1, \dots, N$, investor j faces the problem of optimally choosing m_{ij} to maximize her stage-1 expected utility:

$$U_{1j} = r \left[\sum_{i=1}^N (\beta_{ij} \bar{V}_i - m_{ij}) \right] + \sum_{i=1}^N \lambda_i K_{ij}^*(m_{ij}) + \text{constant} \quad (28)$$

Lemma 2.3. The optimal monitoring effort on firm i exerted by investor j is

$$m_{ij}^* = \begin{cases} \max\left\{0, \beta_{ij}\phi_i + \frac{(\lambda_i - \max_l \lambda_l)\phi_m}{r} - 1\right\} & \lambda_i \neq \max_l \lambda_l \\ \max\left\{0, \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1\right\} & \lambda_i = \max_l \lambda_l \end{cases}$$

where n is the number of firms with $\lambda_i = \max_l \lambda_l$, and λ_i is a firm-level characteristic given in (27).

A few interesting and important properties can be derived from this lemma. First, the optimal monitoring effort of investor j on firm i , m_{ij}^* , is weakly increasing in her initial holdings in this firm, β_{ij} . Everything else being equal, investor j allocates more monitoring effort to firm i if she initially holds a larger fraction of this firm. This is consistent with Shleifer and Vishny (1986) and many others regarding the value of external shareholder monitoring. The second property of optimal monitoring effort is that m_{ij}^* is weakly increasing in ϕ_i , the engagement effectiveness measure. Intuitively, the marginal value of monitoring effort is higher if investors monitor the firms they can more effectively engage with. Since monitoring effort is assumed to enhance firm expected payoffs and is costly, investors will selectively monitor firms that deserve such effort.

Finally, m_{ij}^* is weakly increasing in σ_i via λ_i since $\frac{\partial \lambda_i}{\partial \sigma_i} > 0$ and $\frac{\partial m_{ij}^*}{\partial \lambda_i} \geq 0$. This property indicates that investors optimally make more effort to monitor firms with higher prior uncertainty. This property provides a novel source of motivation for investors to make costly

monitoring effort. Intuitively, since investors inevitably acquire firm-specific information during the process of monitoring a firm and the precision of this piece of firm-specific information, $\kappa(m_{ij})$, is increasing in monitoring effort m_{ij} , investors rationally take into account the beneficial effects of monitoring effort (in stage 1) on total acquired information (in stage 2) when making their monitoring decisions in stage 1. A rational expectations framework allows investors to incorporate considerations of information acquisition into monitoring decisions.

Lemma 2.3 solves the optimal monitoring effort under the first underlying assumption regarding the intrinsic link between monitoring and information acquisition. However, were there no such link, investors would make monitoring effort purely for enhancing firm fundamental values, and the associated allocation of monitoring attention could be pinned down by directly equating marginal benefits and costs of monitoring. We may take this monitoring attention allocation pattern as the benchmark allocation. In the benchmark case, there are no information-acquisition considerations when investors optimally choose monitoring effort for each firm. The benchmark case can be achieved by setting $\phi_m = 0$; that is, $\kappa(m_{ij}) = 0$ regardless of monitoring effort m_{ij} .

Proposition 2.1. Let m_{ij}^{BM} denote the benchmark allocation of optimal monitoring effort to firm i by investor j . Then, $m_{ij}^* \leq m_{ij}^{BM}$ for $\lambda_i \neq \max_l \lambda_l$ and $m_{ij}^* \geq m_{ij}^{BM}$ for $\lambda_i = \max_l \lambda_l$.

Proposition 2.1 compares two different patterns of monitoring effort allocation. Cross-sectionally, the optimal monitoring effort for firms with high (low) marginal value of more precise information is greater (smaller) than the benchmark case. The benchmark case, featured by the absence of the first underlying assumption, describes the allocation of monitoring effort if monitoring only helps enhance firm expected payoffs. That is, there are no considerations of reducing investors' posterior uncertainty via monitoring in the benchmark case. Put differently, compared to the benchmark allocation of monitoring effort, investors

are actually *re-allocating* their monitoring effort from firms with low value of information acquisition to those with high value of information acquisition.⁵¹

I propose the “monitoring-for-learning” mechanism to describe this re-allocation pattern. By rationally anticipating the beneficial effects of monitoring effort on total acquired information, investors optimally make additional monitoring effort onto certain firms and reduce their monitoring effort onto the other firms. This deviation from the benchmark allocation of monitoring effort originates from the rational expectations framework that allows investors to incorporate considerations at later stages into choices at earlier stages. Proposition 1 emphasizes a novel theoretical motivation for investors to undertake costly monitoring activities: monitoring for learning.

Proposition 2.2. Investor j ’s private information precision of firm i , K_{ij} , is weakly increasing in firm i ’s engagement effectiveness measure, ϕ_i .

Proposition 2.2 is an extension of the within-firm complementarity between monitoring and information acquisition. Information acquisition decisions are influenced by how effectively investors engage with firm managers. This proposition suggests that investors acquire more precise information about some of their portfolio firms and less about other ones, depending on how effective it is to engage with corporate executives. This proposition requires empirical evidence to show that an investor is differentially informed about firm subgroups within her portfolio. This differential of information precision enriches the set of feasible empirical tests for information acquisition theory.

Proposition 2.3. Investor j ’s private information precision of firm i , K_{ij} , is weakly increasing in her initial holdings in firm i , β_{ij} .

⁵¹The appendix provides the cross-sectional re-allocation of monitoring effort $\{m_{ij}^* - m_{ij}^{BM}\}_{i=1}^N$.

Proposition 2.3 is also an extension of the within-firm complementarity between monitoring and information acquisition. This proposition suggests that an investor acquires more precise information about the firms in which she has larger ex-ante holdings. Empirically testing this proposition requires evidence for the differential of information precision between large-initial-holdings firms and small-initial-holdings firms within an investor’s portfolio.⁵² Another interpretation of this proposition is to look at the information acquisition patterns among all investors of a given firm. This proposition also suggests that, among all investors of a given firm, the investor subgroup with larger initial holdings in this firm acquire more precise information than the investor subgroup with smaller initial holdings.

Proposition 2.4a. In response to a marginal exogenous increase in firm k ’s ex-ante uncertainty, investor j ’s monitoring effort onto firm i ($i \neq k$) weakly increases if $\lambda_i = \max_l \lambda_l$, and weakly decreases if $\lambda_i \neq \max_l \lambda_l$.

Proposition 2.4b. If the exogenous increase in σ_k is large enough such that λ_k becomes the unique $\max_l \lambda_l$ ex post, then m_{ij} weakly decreases for all $i \neq k$.

Propositions 2.4a and 2.4b show that monitoring and information acquisition activities do not always go hand in hand.⁵³ Depending on the situation in force, m_{ij} either weakly *increases* or *decreases* in response to a marginal increase in σ_k ($k \neq i$); that is, m_{ij} and K_{ij} can go into opposite directions when the exogenous shock to σ_k is marginal.⁵⁴

Proposition 2.4b closely relates to the empirical identification strategy in Kempf, Manconi and Spalt (2017). KMS conjecture that investors’ monitoring attention is re-allocated to firms whose industry is experiencing “attention-grabbing” events. They label experiencing industry-wide extraordinarily volatile returns as attention-grabbing events. Their conjecture

⁵²An information acquisition model without monitoring cannot deliver Propositions 2.2 and 2.3. The marginal value of acquiring more precise information in such models is determined by the ex-ante uncertainty of firm-specific risks rather than initial holdings (or engagement effectiveness).

⁵³ K_{ij} is overall weakly decreasing in σ_k .

⁵⁴Proposition 2.4a is difficult to empirically test.

is consistent with conventional wisdom that it is more rewarding to learn about the more uncertain outcomes. Everything else being equal, firms with high prior uncertainty have high marginal value of learning. However, without clearly distinguishing between monitoring and learning, there still remains a question mark regarding through what channel investors' monitoring attention is attracted to firms experiencing attention-grabbing events.

My work can lend a theoretical support to KMS' identification strategy. In particular, I propose the monitoring-for-learning mechanism to explain that investors make additional monitoring effort onto firms with high value of information acquisition and reduce their monitoring effort onto firms with low value of information acquisition. This monitoring-for-learning story suggests that investors in KMS's framework optimally re-allocate their monitoring effort to firms experiencing industry-wide extraordinarily volatile returns. This re-allocation pattern of monitoring effort is conjectured and empirically tested in KMS.

2.4. *Model Robustness*

2.4.1. *Informational Advantage from Monitoring*

In section 2.2, the intrinsic link between monitoring and information acquisition is modelled in a way that exerting monitoring effort m_{ij} brings investor j with a signal about the firm-specific random component $\tilde{z}_i$ with precision $\kappa(m_{ij})$. The more monitoring effort exerted, the more precise the signal is. To check model robustness, other ways of modelling should be considered regarding the intrinsic link between monitoring and information acquisition. In a realistic sense, during the process of monitoring a portfolio firm, institutional investors may, via board meetings or board members, acquire some "soft information" about CEO ability and internal operating conditions of that firm, which research analysts normally have little access to.

Essentially, this piece of private information acquired during the process of monitoring may be different from the piece of private information acquired by stock analysts in the research department of asset management companies. However, having obtained such soft information can help stock analysts more efficiently produce research reports, resulting in acquiring more precise information about that particular firm. Thus, access to soft information during the process of monitoring can be alternatively modelled as an informational advantage to enable more efficient information acquisition. Appendix B.1 provides the solutions to this modified model and propositions still hold.

2.4.2. Entropy Learning Capacity

In section 2.2, a linear constraint of information processing capacity is employed following Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). In their online appendix, entropy learning capacity is also checked to ensure propositions to hold.⁵⁵ Essentially, a linear learning capacity constrains the sum of signal precisions while an entropy learning capacity constrains the product of signal precisions (Veldkamp (2011, p.21)). Appendix B.2 provides the solutions to the 3-stage model where investors face entropy learning capacity constraints. Propositions still hold in this modified framework.

2.5. Model Predictions

Subgroups of firms or of investors are in need to empirically quantify investors' information acquisition activities, and this section focuses on deriving model predictions from propositions and constructing empirical measures for model predictions.

Prediction 2.1a Investors tend to have more precise information about the firms they have higher initial holdings in.

⁵⁵Sims (2003), Mondria (2010), and Maćkowiak and Wiederholt (2009, 2015) provide the applications of entropy-based constraints in economics and finance.

Prediction 2.1b Among all investors of a given firm, the investor subgroup with high initial holdings in this firm tend to have more precise information than the investor subgroup with low initial holdings.

These “two-way” predictions are derived from Proposition 2.3. Prediction 2.1a says that, within a given investor’s portfolio, this investor is predicted to have more precise information about firms in the firm subgroup of high initial holdings than in the other firm subgroup. This is the within-portfolio prediction regarding initial holdings. Prediction 2.1b says that, among all investors of a given firm, there is a differential in information precision between the investor subgroup with high initial holdings in this firm and the other investor subgroup. This is the within-firm prediction regarding initial holdings.

Prediction 2.2 Investors tend to have more precise information about the firms they can more effectively engage with.

This prediction is derived from Proposition 2.2. Prediction 2.2 says that, within a given investor’s portfolio, there is a differential in her information precision between the firm subgroup she can more effectively engage with and the other firm subgroup. Predictions 2.1a and 2.2 suggest the joint pattern of information acquisition and determinants of monitoring effort across the firms of an investor’s portfolio.

Prediction 2.3 Information precision is negatively related to reduced monitoring intensity.

This prediction is derived from the within-firm complementarity between monitoring and information acquisition. This complementarity suggests, given an exogenous decrease in investor j ’s monitoring effort on firm i , her information precision of firm i decreases even after controlling for firm- i or investor- j characteristics. Prediction 2.3 intends to show the positive relation between K_{ij} and m_{ij} via providing evidence that ΔK_{ij} is negatively related

to $-\Delta m_{ij}$. The next section shows how to construct the empirical counterpart for $-\Delta m_{ij}$, the reduced monitoring intensity on firm i by investor j .

Prediction 2.4 Monitoring intensity is positively related to engagement effectiveness and negatively related to shareholder distraction.

This prediction is derived from the formula for optimal monitoring effort in Lemma 2.3 and the re-allocation pattern of monitoring effort in Proposition 2.1 by aggregating “firm-investor” level parameters into firm level parameters. An investor’s monitoring effort on firm i will decrease in response to an exogenous increase to another firm’s ex-ante volatility. This exogenous increase to another firm’s ex-ante volatility is a form of distraction to all investors holding firm i . Since all investors holding firm i need to face the distraction due to this exogenous volatility increase, then the firm-level aggregated monitoring effort from all investors of firm i decreases as well. This firm-level monitoring effort aggregated across all investors is also predicted to be increasing in engagement effectiveness. The empirical section uses contested voting activities at annual general meetings as proxy for (endogenous) monitoring intensity.

2.6. Data Description

Datasets from several sources are employed in the empirical section. First, data of stock holdings by institutional investors at the quarterly frequency are obtained from Thomson Reuters’ institutional holdings (which used to be known as the CDA/Spectrum holdings database). Institutional investors are required to file 13f forms with the Securities and Exchange Commission (SEC) to report their equity holdings if their asset under management exceeds \$100m or if other conditions are triggered.⁵⁶ Complementary data of institutional investors classify institutional investors into three groups: transient, dedicated, and quasi-

⁵⁶Further detailed information about Form 13f with the SEC can be found via: <https://www.sec.gov/fast-answers/answers-form13fhtm.html>

index tracking.⁵⁷ I exclude institutional investors that are classified as quasi-index tracking from my sample due to their passive investing nature.

Second, the dataset of scaled wealth-to-performance sensitivity is from Edmans, Gabaix and Landier (2009).⁵⁸ This dataset provides the ex-ante sensitivity of executives' compensation in response to share price, which is properly scaled for cross-sectional comparability among different firms. Using this sensitivity measure as proxy for engagement effectiveness is consistent with the theoretical literature of external governance: The executives care more about external shareholders' "voice" or "threat of exit" if their compensations are highly sensitive to their firm's share price. This "share price" channel is also consistent with McCahery, Sautner and Starks (2016) deriving evidence, using surveys among professional fund managers, that managerial equity-based ownership/grant is one important factor to consider when institutional shareholders make decisions of whether to proactively engage with firm management.

Data of contested voting activities is from Institutional Shareholder Services (ISS). Following Cunat, Gine and Guadalupe (2012), I focus on shareholder-sponsored proposals that are eventually voted at annual general meetings (AGM). In particular, I follow their definition of contested voting activities as passing or failing a shareholder proposal by less than a 5% margin around the passing threshold. For example, if the passing threshold is 0.5, then shareholder proposals with a voting outcome ranging from 0.45 to 0.55 will be classified as contested. The indicator variable, *ContestMeeting*, takes the value of one if there is at least one shareholder proposal with contested voting activities, and zero otherwise. It is feasible

⁵⁷The methodology of classifying institutional investors as transient, dedicated, and quasi-index tracking can be found in Bushee (1998) and is further developed in Bushee and Noe (2000) and Bushee (2001). As described in these papers, briefly, transient institutional investors hold relatively well-diversified portfolios but actively trade, aiming at short-run gains; dedicated institutional investors hold relatively concentrated portfolios but do not often trade, aiming at long-run gains; quasi-index tracking institutional investors largely replicate the returns of market-level or industry-level indices.

⁵⁸Professor Alex Edmans generously shares data of the scaled wealth-to-performance sensitivity via his personal website: <http://alexedmans.com/data/>, and detailed information regarding empirical measure construction can be found in Appendix B of Edmans, Gabaix and Landier (2009).

to argue that contested voting activities at AGMs occupies valuable resources from shareholders and thus can serve as a good proxy for endogenous monitoring intensity in Prediction 4 at the firm level.

2.7. Measure Construction and Summary Statistics

One challenge to test model predictions is of empirically measuring precision of private information as stock-picking ability. I take the following approach. First, I calculate the percentage change in the holdings of a firm from time $t - 1$ to time t as $\Delta q_t/q_{t-1}$. Second, I calculate standardized unexpected earnings (SUE) using the difference between announced earnings and earnings forecast following the SUE literature in Accounting and Finance. Data of analyst earnings forecast are obtained from I/B/E/S. This difference is then scaled by share price at the previous quarter end. Finally, I calculate a score to measure how the percentage changes in individual firm holdings from quarter to quarter covariate with next-period earnings surprises; that is,

$$StockPickingAbility_{gt} = \frac{1}{N_{gt}} \sum (\Delta q_t/q_{t-1}) * SUE_{t+1} \quad (29)$$

where g indexes a particular subgroup of firms or of investors.

This measure directly speaks to the its theoretical counterpart $E \left[\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right) \tilde{z}_i \right]$, where $\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right)$ is the theoretical counterpart for $(\Delta q_t/q_{t-1})$, and $\tilde{z}_i$ for SUE_{t+1} . The theoretical counterpart for this stock-picking ability measure is an increasing function of K_{ij} .⁵⁹ Investors with a high score of stock-picking ability tend to adjust their holdings in advance of earnings surprises, and these in-advance adjustments tend to be in the same direction with next-period earnings surprises. This measure of stock picking ability is the dependent variable for most of the regression analyses.⁶⁰ This measure of stock picking ability uses next-period earnings

⁵⁹Detailed derivation can be found in Appendix B.3.

⁶⁰When directly testing the within-firm complementarity between monitoring and information acquisition in a panel-regression setup, $((\Delta q_t/q_{t-1}) * SUE_{t+1})_{ijt}$ is the dependent variable at the level of firm i , investor

surprises as proxy for firm-specific information $\tilde{z}_i$. I also consider using holding period return in excess of market return for the next period as proxy for firm-specific information $\tilde{z}_i$.⁶¹

To generate $\Delta q_t/q_{t-1}$ from quarterly holdings data of individual institutional investors, I first “blockfill” an entry for firms an institutional investor has ever held throughout the sample period. That is, I enter a holding of zero for a particular firm if an institutional investor does not hold it for the current quarter. This ensures a full time series for each firm that has ever been held by a given institutional investor. Then, I generate $\Delta q_t/q_{t-1}$ as the first difference scaled by last-period holding in a particular firm by this investor. To properly deal with the missing values generated, I further replace $\Delta q_t/q_{t-1}$ with 1 if $q_{t-1} = 0$ but $q_t > 0$ and replace $\Delta q_t/q_{t-1}$ with 0 if both $q_{t-1} = 0$ and $q_t = 0$. This replacement assigns a 100% $\Delta q_t/q_{t-1}$ towards firms that are first time held by an institutional investor with a zero holding in the previous quarter. Continuously having a zero holding in a firm will have zero contribution to the measure of stock picking ability.

Three alternative measures of stock picking ability are generated for comparisons in Tables 2.1 and 2.2. These three measures slightly differ from each other regarding how to deal with $\Delta q_t/q_{t-1}$. For example, In Table 2.1, Panel A winsorizes $\Delta q_t/q_{t-1}$ at 1% level each tail, Panel B upper-bounds $\Delta q_t/q_{t-1}$ with 1, Panel C uses the raw measure of $\Delta q_t/q_{t-1}$. All three approaches need to follow (29) to finally generate measures of stock picking ability by multiplying SUE , summed across a particular subgroup of firms or of investors, and then scaled by the number of entities in this subgroup. Naturally, the standard deviation of the bounded measure is smallest (1.967 for Single Sort and 1.952 for Double Sort), then the winsorized measure (2.795 for Single Sort and 3.105 for Double Sort), and the standard deviation of the raw measure is wild because of many extreme values (1551.6 for Single Sort and 2700.6 for Double Sort). Similar results can be obtained from Table 2.2.

j and time t .

⁶¹Main results replicated using this return-based measure can be found in Tables A3.1, A3.2, and A3.6.

2.8. *Summary of Chapter Two*

This chapter provides a new layer of theoretical motives for investors to make costly monitoring effort beyond traditional determinants of shareholder monitoring. The monitoring-for-learning mechanism proposed in this chapter describes the re-allocation pattern of monitoring effort from certain firms to the others if compared to the benchmark case. This new layer of theoretical motives, linking information acquisition and determinants of monitoring effort, has empirical implications for shareholder stock-picking ability.

The model predicts that investors optimally acquire more precise information about the firms they can more effectively engage with and about those they have larger initial holdings in. These within-portfolio predictions suggest an investor be better informed about one subgroup of firms within her portfolio than the other, depending on firms' engagement effectiveness and her initial holdings. The model also suggests that among all investors of a given firm, those with high initial holdings in this firm tend to have more precise information than those with low initial holdings. This within-firm prediction suggests subgroups of investors holding a firm be differentially informed about this firm, depending on their initial holdings. Additional predictions regarding information acquisition and monitoring intensity are derived from propositions.

3. Chapter Three

3.1. *Related Literature and Contributions*

My work in this chapter relates to the empirical literature of costly monitoring activities by US institutional investors⁶² and the literature documenting that institutional investors possess informational advantages and make better informed portfolio decisions⁶³. These two streams of literature motivate the joint capacity constraint of monitoring and information acquisition as set up in my work, making it possible to further explore their within-firm and cross-firm interactions. The Investor Responsibility Research Center Institute (2011) widely surveyed US institutional investors and firms, suggesting that time and personnel considerations rank as the top two factors impeding effective engagement between institutional investors and portfolio firms.⁶⁴

Most importantly, this chapter closely relates to Kempf, Manconi and Spalt (KMS onwards) (2017) where they propose a new empirical approach to identify the re-allocation pattern of monitoring attention for institutional investors.⁶⁵ Since the major contributions of KMS are on the empirical side, their theoretical framework for empirical identification does not allow for a clear distinction between investor attention for monitoring and investor attention for information acquisition. KMS's empirical identification strategy requires a framework where attention for monitoring is squeezed among certain firms when acquiring

⁶²Brickley, Lease and Smith (1988), Agrawal and Mandelker (1990), Del Guercio and Hawkins (1999), Borokhovich et al. (2006), Chen, Harford and Li (2007), Cornett et al. (2007). Becht, Franks, Mayer and Rossi (2009) provide evidence of monitoring activities conducted by UK institutional investors.

⁶³Institutional investors are documented to possess informational advantages around dividend announcements (Amihud and Li (2006)), in seasonal equity offerings (Chemmanur, He and Hu (2009)), or in events of stock splits (Chemmanur, Hu and Huang (2015)), or hold both corporate debt and equity of the same firms as “dual holders” (Jiang, Li and Shao (2010), and Ivashina and Sun (2011)).

⁶⁴This chapter does not touch the relation between stock market liquidity and the (opportunity) cost of monitoring portfolio firms. Maug (1998), Bolton and von Thadden (1998), Almazan, Hartzell and Starks (2005), and Back et al. (2016) consider stock market liquidity as a factor that impacts external governance.

⁶⁵KMS argue that monitoring attention is re-allocated to firms whose industries are experiencing “attention-grabbing” events such that the other firms facing reduced monitoring pressure tend to announce value-destroying acquisitions, cut dividends, and so on. Additionally, they find that CEOs of firms facing reduced monitoring pressure are less likely to be fired for delivering bad performance. They argue for the disciplining effects of shareholder monitoring on corporate actions.

more precise information is highly rewarding among other firms due to exogenous changes in the prior uncertainty of these other firms. My model can deliver such features. In my model, investors optimally make more effort to monitor firms with higher prior uncertainty and optimally reduce their monitoring effort on a firm in response to shocks to other firms' prior uncertainty. This cross-sectional re-allocation pattern of monitoring effort lends a theoretical support to KMS's empirical strategy.

The rest of this chapter proceeds as follows. Section 3.2 provides empirical evidence for model predictions regarding stock picking ability and percentage holdings by institutional investors. Section 3.3 presents empirical evidence for model predictions regarding stock picking ability and engagement effectiveness. Section 3.4 provides empirical evidence regarding the within-firm complementarity between monitoring and learning as proposed in the previous chapter. Section 3.5 presents empirical evidence regarding the relation between contested voting activities and shareholder distraction, and Section 3.6 summarizes this chapter.

3.2. *Stock Picking Ability and Percentage Holdings*

Empirically testing Prediction 2.1a requires evidence regarding the differential in stock-picking ability between two subgroups of firms within an investor's portfolio. For each institutional investor at each quarter, I first sort all her portfolio firms into two subgroups, depending on her percentage holdings in these individual firms in the previous quarter.⁶⁶ Then, I calculate a score of stock-picking ability for each subgroup. Panel A in Table 3.1 shows that investors tend to have higher scores of stock-picking ability among the firms they have high initial holdings in relative to those they have low initial holdings in. Specifically, the average score of stock-picking ability is 3.031 for *High Initial Holdings*, which is higher than the average score of stock-picking ability, 0.224, for *Low Initial Holdings*. The differential

⁶⁶I also consider sorting all firms she holds by the portfolio weight of individual firms in her portfolio. Main regression results using percentage holding are replicated in Tables A3.7 and A3.8 using a firm's portfolio weight for robustness check.

in stock-picking ability between *High Initial Holdings* and *Low Initial Holdings* is 2.807 and statistically significant at the 1% level. This differential is economically significant as well if compared with the sample standard deviation of 2.795.

[Insert Table 3.1 near here]

I further control for the ex-ante volatility of portfolio firms to mitigate concerns regarding its impacts on information acquisition. This is due to the feature that ex-ante volatility determines the marginal value of more precise information, which drives both conducting independent research and monitoring. I use the realized volatility of a firm's daily returns in the previous quarter to serve as proxy for ex-ante volatility. Heterogeneity in ex-ante volatility is controlled for via a sequential sorting on realized volatility first and then on initial holdings. For each institutional investor at each quarter, I first sort all her portfolio firms into five ranks from *Low Volatility* to *High Volatility*, depending on individual firms' ex-ante volatility. Then, I further sort all firms within each rank into two subgroups based on her initial holdings. Thus, for each institutional investor at each quarter, I calculate a score of stock-picking ability for each of these ten subgroups of firms. Clearly, we can see from Panel A in Table 3.1 that the average score of stock-picking ability among *High Initial Holdings* subgroups is statistically significantly higher than the average score of stock-picking ability among *Low Initial Holdings* subgroups. This pattern holds for all five ranks of ex-ante volatility with differentials in the magnitudes ranging from 2.867 to 3.464. Heterogeneity of stock-picking ability has been absorbed at the investor-by-year-quarter level. These differentials are economically significant as well if compared with the sample standard deviation of 2.527.

Empirically testing Prediction 2.1b requires evidence regarding the differential in stock-picking ability among subgroups of investors holding a given firm. Looking at all investors holding a given firm is another useful way to mitigate concerns regarding the compounding

impacts of firm ex-ante volatility on investors’ acquired information precision. For each firm at each quarter, I first sort all investors into five subgroups *Low Initial Holdings (IH)* to *High IH*, depending on their percentage holdings in this firm in the previous quarter. Then, I calculate a score of stock-picking ability for each investor subgroup. Panel A in Table 3.2 shows that the average score of stock-picking ability monotonically increases from *Low IH* to *High IH*. The statistical significance in Table 3.2 is relative to the *IH3* subgroup, the investor subgroup with medium level of initial holdings in a firm. Column (1) presents OLS regression results with robust standard errors. Column (2) clusters standard errors at the firm level and includes firm fixed effects. Column (3) instead includes “firm by year-quarter” fixed effects.⁶⁷ These differentials are of economic significance as well if compared with the sample standard deviation of 1.905.

[Insert Table 3.2 near here]

Possessing privileged access to private information due to substantial holdings in a firm can be a threat to the empirical evidence indicating higher stock-picking ability of the investor subgroup with high percentage holdings in a firm. To illustrate this concern, I use Regulation Fair Disclosure (or “Reg FD”), a regulatory change introduced in August 2000 by SEC, as a feasibly exogenous shock to firms’ information environment in the US equity markets. Before Reg FD, firm management may selectively release “material non-public” information to certain institutional shareholders, stock analysts, broker-dealer firms, and so on. This practice raised frustration among retail investors and other market participants that were placed at a disadvantageous position. Receivers of such material non-public information were very likely to make profits, or avoid losses, based on their received information via firm management’s selective disclosure. Receivers of material non-public information via selective disclosure were in effect taking advantages of those “kept in the dark” before exactly the

⁶⁷Including such high-dimensional fixed effects is equivalent to including a comprehensive list of firm characteristics, both observable and unobservable, that are relevant for stock-picking ability.

same information was released to the public. This is the Pre-2000 regime.

After Reg FD was introduced in August 2000, SEC requires firm management to simultaneously release the same information to the public via non-exclusive and well-circulated news wires, press releases, and other viable means for intentional disclosure of material non-public information. Non-intentional disclosure of such information must be released to the public “promptly” (i.e. within 24 hours). Reg FD has been argued to effectively remove the “nonerodable informational advantages” that used to be enjoyed by the privileged group in the Pre-2000 regime. This regulatory change provides an opportunity to compare the effects of percentage holdings in a given firm on investors’ stock-picking ability.

[Insert Figure 3.1 near here]

Following Borochin and Yang (2017), I use the five-year subsamples before and after 2000, exclusive. In particular, following Borochin and Yang (2017), I use the 1999Q4 information of investor’s percentage holdings in a given firm to classify an investor into one of the five subgroups, from low to high percentage holdings in a firm.⁶⁸ Figure 3.1 provides empirical evidence regarding Reg FD. The vertical axis of Figure 3.1 measures stock-picking ability of investor subgroups, along the horizontal axis, from low to high percentage holdings in a firm. The blue bars are for the Pre-2000 regime and the grey bars for the Post-2000 regime.

We can see that both Pre-2000 and Post-2000 regimes suggest that investor’s stock-picking ability increases from low to high percentage holdings. This supports the within-firm prediction regarding stock-picking ability and percentage holdings in a firm. More interestingly, the blue bars present an upward but far steeper slope along the horizontal axis, whereas the grey bars, though still upward-sloping, are much flatter. These patterns, if put altogether, jointly indicate that investor’s stock-picking ability increases as their percentage holdings in

⁶⁸This rules out the possibility that an investor may “switch” from one subgroup to another in response to the adoption of Reg FD.

a firm increases and that Reg FD has effectively removed the privileged access to private information enjoyed by shareholders with substantial holdings in a firm. Robustness checks are conducted using alternative Pre-2000 subsamples.

3.3. *Stock Picking Ability and Engagement Effectiveness*

Similar to Prediction 2.1a, empirically testing Prediction 2.2 requires evidence regarding the differential in stock-picking ability between two subgroups of firms within an investor's portfolio but now depending on firm-level engagement effectiveness measure. For each institutional investor at each quarter, I first sort all her portfolio firms into two subgroups, depending on how effectively she can engage with firm management. The scaled wealth-to-performance sensitivity measure serves as a proxy for engagement effectiveness. Then, I calculate a score of stock-picking ability for each subgroup of firms. The first row of Panel A in Table 3.3 shows that the average score of stock-picking ability in the *High Engagement Effectiveness* subgroup is statistically significantly higher than that in the *Low Engagement Effectiveness* subgroup. The economic significant, however, needs further discussion.

[Insert Table 3.3 near here]

Again, to further control for ex-ante volatility of portfolio firms, I first sort an investor's portfolio firms into five ranks, depending on individual firms' ex-ante volatility. Then, portfolio firms within each ex-ante volatility rank are sorted into two subgroups. Thus, for each institutional investor at each quarter, all her portfolio firms are sorted into ten subgroups. We can see from the last five rows of Panel A in Table 3.3 that sorting firms based on engagement effectiveness statistically significantly matters in four out of five ex-ante volatility ranks. Overall, Table 3.3 confirms model prediction regarding information precision and firm-level engagement effectiveness. Heterogeneity of stock-picking ability has been absorbed at the investor-by-year-quarter level.

3.4. *Within-firm Complementarity between Monitoring and Learning*

Empirically testing the within-firm complementarity between monitoring and information acquisition requires observations at the firm-investor level. Thus, I use the product between investor j 's percentage change in the holdings of firm i and the next-period earnings surprise firm i as the proxy for her stock-picking ability in firm i . The main explanatory variable, *Distraction*, is the investor-specific component of firm-level distraction score constructed in Kempf, Manconi and Spalt (2017). Both variables are at the firm-investor level for each quarter. This component of firm-level distraction score is feasibly exogenous because distraction, or reduced monitoring effort, results from shocks to other firms within an investor's portfolio.

[Insert Table 3.4 near here]

Panel A of Table 3.4 shows that investors' stock-picking ability decreases in response to distraction caused by other firms within their portfolios. This negative relation is statistically significant when clustering standard errors at the firm level and including fixed effects at the level of firm, firm by year-quarter, investor by year-quarter, and firm by investor, respectively, for columns 2 to 5. Panel B of Table 3.4 further explores the relation between first difference in investors' stock-picking ability and distraction. This strictly follows the within-firm complementarity between monitoring and information acquisition: $\frac{\partial K_{ij}}{\partial m_{ij}} \geq 0$ for $i = 1, \dots, N$. In this empirical setup, *Distraction* is the empirical counterpart of $-\Delta m_{ij}$, the reduced monitoring intensity at firm-investor level; *d_PS* is the empirical counterpart of ΔK_{ij} . Panel B shows that the first difference in investors' stock-picking ability is negatively correlated with the reduced monitoring intensity. The more distracted investor j from firm i to other firms, the less precise her information about firm i . Standard errors and fixed effects follow those in Panel A.

3.5. *Contested Voting Activities and Shareholder Distraction*

I use contested voting activities at annual general meetings (AGMs) as proxy for shareholders' monitoring intensity. Following Cuñat, Gine and Guadalupe (2012), I define a contested proposal as one voted to either pass or fail by a 5% margin around the threshold. Table 3.5 present some key figures to get a general idea of proposal votings. In Panel A, we can see that only less than 1% of all voted proposals are contested. This may indicate that contested voting activities at AGMs are not very common and are very likely to occupy shareholders' resources of time and personnel. I check that the voting outcomes for contested proposals are close to 50-50, consistent with the small margin around the threshold. However, the vast majority of uncontested proposals are voted to pass, indicating the importance of looking into the sponsorship type of proposals.

[Insert Table 3.5 near here]

Panel B of Table 3.5 shows that more than 95% of all voted proposals are actually sponsored by firm management and less than 5% by shareholders.⁶⁹ This indicates that voting activities of shareholder proposals can be a good candidate to measure the monitoring intensity at the firm level. Further looking into the voting activities of shareholder proposals, we can see that nearly 10% of shareholder proposals experience contested voting activities by shareholders. This is in sharp contrast with the less-than 1% contested voting activities out of all proposals, including both management-sponsored and shareholder-sponsored proposals. Finally, we can clearly tell the general attitude of how firm management views shareholder proposals. Panel C of Table 3.5 shows firm management recommends voting against more than 97% of shareholder proposals while recommending voting for more than 99% of management proposals. Therefore, I use contested voting activities at a firm's AGM as proxy for firm-level monitoring intensity by shareholders.

⁶⁹KMS (2017) shows that a firm's shareholders are less likely to sponsor proposals when they are largely distracted to focus on other firms in their portfolios.

Table 3.6 presents empirical evidence for the monitoring-for-learning mechanism I have proposed in Chapter Two. This mechanism describes the re-allocation pattern of monitoring effort across firms. All variables in Table 3.6 are at the firm-year level. The dependent variable, *ContestMeeting*, equals one if there are contested voting activities in a firm’s shareholder proposals at AGM, and zero otherwise. Contested voting activities are defined following Cuñat, Gine and Guadalupe (2012). *ScaledWPS_sort* is a ranking variable based on the scaled wealth-to-performance sensitivity in Edmans, Gabaix and Landier (2009). *Distraction* is constructed as in Kempf, Manconi and Spalt (2017). *Mkt_cap* takes the natural log of a firm’s market capitalization at the quarter end prior to a firm’s AGM. *Turnover* is the stock trading turnover defined as the ratio of trading volume over number of shares outstanding at the previous quarter end. *Ret_q* is the quarterly holding-period return at the previous quarter end. *Momentum_9* is the 9-month return during the [-12m, -3m] period. *R_vol_q* is the realized volatility of daily returns in the previous quarter.

[Insert Table 3.6 near here]

Table 3.6 shows that contested voting activities are more likely to occur to firms with higher scaled wealth-to-performance sensitivity. These are the firms investors can more effectively engage with. The “re-allocation” effects on monitoring effort are confirmed with the negative coefficient of *Distraction*. The more distracted a firm’s institutional shareholders, the *less* monitoring intensity on this firm jointly by this firm’s institutional shareholders, and therefore, the less likely for contested voting activities to occur at this firm’s AGM. These two coefficients are statically significant in OLS regressions with robust and clustered standard errors and the Probit regression as well. Year fixed effects are included in all specifications. Empirical results with alternatively defined control variables can be found in the supplementary appendix.

3.6. Summary of Chapter Three

In this chapter, I construct empirical measures of stock-picking ability as proxy for precision of acquired information and scaled wealth-to-performance sensitivity (ScaledWPS) from Edmans, Gabaix and Landier (2009) as proxy for engagement effectiveness. Empirical evidence shows that institutional investors tend to have higher scores of stock-picking ability among firms with high ScaledWPS than firms with low ScaledWPS. They also tend to have better stock-picking ability among firms they have high initial holdings in than firms they have low initial holdings in. Put differently, for the same institutional investor, she is better able to pick the right stocks among one subgroup of firms than the other subgroup. In addition to the within-portfolio evidence above, I find that, among all institutional investors holding a firm, the subgroup of investors with high initial holdings in this firm tend to have a higher score of stock-picking ability than the subgroup with low initial holdings.

To mitigate concerns of shareholders with high percentage holdings in a firm having privileged access to material non-public information, I use Reg FD as an exogenous shock to the information environment of US stock markets. The empirical evidence broadly confirms the importance of percentage holdings in a firm to stock-picking ability in both Pre-2000 and Post-2000 subsamples. However, comparing the 5 years before and after 2000, exclusive, empirical evidence indicates that percentage holdings in a firm matters more for stock-picking ability in the Pre-RegFD regime and matters less in the Post-RegFD regime. This finding is consistent with firm management selectively disclosing material non-public information to shareholders with privileged access to such information in the Pre-RegFD regime. This finding also supports that Reg FD effectively removes such privileged access to material non-public information due to the Pre-RegFD practice of selective disclosure by firm management.

Next, this chapter explores the empirical relation between change in stock-picking ability and change in monitoring intensity at investor-firm level at the quarterly frequency. This empirical relation serves as a direct test on the within-firm complementarity between monitoring and information acquisition. The investor-specific component of the firm-level shareholder distraction score, as constructed in Kempf, Manconi and Spalt (2017), serves as the empirical counterpart of the decrease in monitoring intensity due to feasibly exogenous shocks to other firms within an investor's portfolio. The empirical evidence indicates that change in stock-picking ability is negatively correlated with the decrease in monitoring intensity, i.e. shareholder distraction. This negative correlation between change in stock-picking ability and the decrease in monitoring intensity supports the within-firm complementarity between monitoring and information acquisition.

Finally, this chapter uses contested voting activities at a firm's annual general meeting as proxy for firm-level monitoring intensity. This firm-level monitoring intensity is the empirical counterpart of the aggregated monitoring effort among all investors holding this firm. I find supportive firm-level evidence for the re-allocation pattern of monitoring effort: Contested voting activities at annual general meetings are more likely to occur to firms with which investors can more effectively engage and less likely to occur to firms whose institutional shareholders are largely distracted. This firm-level evidence is consistent with the monitoring-for-learning mechanism I propose and the properties of optimal monitoring effort as solved in the model.

4. Concluding Remarks

Economic agents have limited capacity to collect high-quality private information about uncertain factors that are essential to better decision making. How to optimally allocate this limited resource, or put differently, the endogenous choices of information acquisition, has been extensively studied in the theoretical literature of information acquisition. However, how to test such theories can be empirically challenging because information choices are usually unobservable. Veldkamp (2011) suggests that researchers circumvent this problem by linking information choices with observables, for example, portfolio choices, states of the business cycle, and so on.

My doctoral thesis focuses largely on extending existing theories of endogenous information acquisition as a building block and delivers new predictions for empirical tests. **Chapter One** theoretically explores and empirical examines the roles of macroeconomic announcements when investors digest firm-earnings news. The starting point is that informational efficiency of individual firms is endogenously determined by investors' information acquisition behavior. Then, the two competing features of macroeconomic announcements have been discussed and properly incorporated into one rational expectations framework. I propose the "attention re-allocation mechanism" and confirm the distracting effects of macroeconomic announcements prior to being released and their complementary effects upon being released on informational efficiency of individual firms. My model further predicts that these effects are more (less) pronounced during expansions (recessions). Empirical evidence is provided to support model predictions.

Chapter Two starts with in-depth discussions regarding the distinctions and links between monitoring and information acquisition. Briefly, monitoring a firm has two separate but related effects: enhancing firm expected payoff and reducing uncertainty in firm-specific risk. These two effects are related via the premise that investors actually acquire private

information about a firm during the process of monitoring it. Nonetheless, investors may choose to exert no monitoring effort but instead conduct independent research to collect private information about that firm. That is, conducting independent research also reduces uncertainty in firm-specific risk. My model employs an informational structure where an investor's total acquired private information about a certain firm comes from two sources: (i) private information acquired via monitoring a firm, and (ii) private information acquired via conducting independent research. Naturally, private information from either source is helpful when making portfolio choices.

This informational structure allows investors to flexibly choose how much monitoring effort to make onto individual firms and how much additional private information to acquire via conducting independent research. Under certain conditions, an investor may choose to make zero monitoring effort onto a firm but acquire high-precision private information about the firm via conducting independent research. My model can also accommodate cases where an investor may choose to make substantial monitoring effort onto a firm but not want to acquire any additional private information about the firm via conducting independent research. This flexibility enables the model to better describe the reality of how institutional investors may have to allocate a fixed amount of valuable resources between monitoring and learning.

Chapter Three presents empirical evidence to examine the predictions of **Chapter Two**. Empirical evidence regarding engagement effectiveness confirm the prediction that investors tend to have better stock-picking ability among firms they can more effectively engage with. I use the scaled sensitivity measure of executive compensation to firm share price to serve as proxy for engagement effectiveness. Empirically, I also find that investors tend to have better stock picking ability among firms they have high initial holdings in than firms they have low initial holdings in. Along another dimension, that is, among all institutional investors holding a firm, the subgroup of investors with high initial holdings in this firms tend to have a higher score of stock-picking ability than the subgroup with low

initial holdings. Additional evidence is provided for further discussions.

Broadly speaking, these chapters are essentially extensions of existing theories of endogenous information acquisition into two directions, namely, informational efficiency of individual firms, and stock-picking ability within an investor's portfolio. Basically, there are many investors holding the same firm while each investor holds many firms in her portfolio. Once figuring out the endogenous choices of information acquisition by an investor, we can have it aggregated across all investors and obtain firm-level implications. This is the method of **Chapter One**. If focusing on the firms within one investor's portfolio, we can theoretically explore the cross-sectional re-allocation of monitoring effort and therefore total information acquired for each portfolio firm. This is the method of **Chapter Two**, which theoretically motivates the empirical tests in **Chapter Three**.

Appendix A. Proofs of Chapter One

A.1. Lemma 1.1. Equilibrium Prices

Equilibrium price of risk factor i is conjectured to take the linear form (Admati (1985) and many others), for $i = 1, \dots, N$:

$$p_i = 0 + \mu_2 \tilde{Z}_i + \mu_3 (1 + x_i) \quad (30)$$

Rescaling the price signal into:

$$\tilde{s}_i = \frac{p_i}{\mu_2} = \tilde{Z}_i + \frac{\mu_3}{\mu_2} (1 + x_i) \quad (31)$$

Please note that p_i and $\tilde{s}_i$ contains the same information. The precision of this rescaled price signal is $\frac{\mu_2^2}{\mu_3^2} \gamma$. Then applying Bayesian updating to form investor j 's posterior beliefs:

$$E_j \left(\tilde{V}_i \right) = \frac{0 + K_{ij} \left(\tilde{Z}_i + \epsilon_{ij} \right) + \frac{\mu_2^2}{\mu_3^2} \gamma \tilde{s}_i}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma} \quad (32)$$

$$Var_j \left(\tilde{V}_i \right) = \frac{1}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma} \quad (33)$$

Plugging (32) and (33) into (7) gives:

$$q_{ij} = \frac{1}{\rho} \left(0 + K_{ij} \left(\tilde{Z}_i + \epsilon_{ij} \right) + \frac{\mu_2^2}{\mu_3^2} \gamma \tilde{s}_i - r p_i \left(\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma \right) \right) \quad (34)$$

The market clearing condition for risk factor $i = 1, \dots, N$:

$$\int_0^1 q_{ij} dj = 1 + x_i \quad (35)$$

Rearranging the terms delivers the equilibrium price of firm i as a linear function of $\tilde{Z}_i$ and $(1 + x_i)$ ⁷⁰:

$$p_i = \frac{0 + \left(K_{ij} + \frac{\mu_2^2}{\mu_3^2}\gamma\right) \tilde{Z}_i + \left(\frac{\mu_2}{\mu_3}\gamma - \rho\right) (1 + x_i)}{\alpha_i + \bar{K}_i + \frac{\mu_2^2}{\mu_3^2}\gamma} \quad (36)$$

The coefficients of $\tilde{Z}_i$ and $(1 + x_i)$ in (36) contain μ_2 and μ_3 , which can be solved by matching the coefficients in (30) and (36). Specifically,

$$\mu_2 = \frac{\bar{K}_i + \frac{\bar{K}_i^2}{\rho^2}\gamma}{r \left(\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2}\gamma \right)} \quad (37)$$

$$\mu_3 = -\frac{\left(\frac{\bar{K}_i}{\rho}\gamma + \rho\right)}{r \left(\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2}\gamma \right)} \quad (38)$$

This is Lemma 1.1.

A.2. Lemma 1.2 and Proposition 1.1.

This section provides the detailed solution to the model that accommodates the releases of macroeconomic announcements into Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) as all investors receiving a free but informative signal about the aggregate risk with a given precision $K_{MA} > 0$.

Recall that $\bar{K}_N^O$ denotes the average attention allocation to the aggregate risk subject to constraints (3) and (4), and $\bar{K}_N$ the allocation subject to constraints (12) – (14). Mathematically, $\bar{K}_N^O = \int_0^1 K_{Nj}^O dj$ and $\bar{K}_N = \int_0^1 K_{Nj} dj$. That is, $\bar{K}_N^O$ represents how much attention an average investor would have allocated to the aggregate risk were there no macroeconomic announcement (“the original equilibrium allocation”); $\bar{K}_N$ represents the average

⁷⁰One useful result to mention is $\int_0^1 K_{ij} \epsilon_{ij} dj = \int_0^1 K_{ij} dj \int_0^1 \epsilon_{ij} dj = 0$. This is due to the fact that K_{ij} and ϵ_{ij} are linearly uncorrelated.

attention allocated to the aggregate risk after a macroeconomic announcement is released, and all investors make their attention allocation decisions after taking this macroeconomic announcement into account (“the new equilibrium allocation”).

If the aggregate risk is the absolutely dominating risk source in the sense that λ_N is high enough to be the unique $\lambda = \max_l \lambda_l$ even after fully incorporating K_{MA} into $\bar{K}_N$, then $\bar{K}_N$ increases exactly by the amount of K_{MA} from $\bar{K}_N^Q$. That is, $\bar{K}_N = \bar{K}_N^Q + K_{MA}$. In this case, the magnitude of the crowding-out effect is zero: The full amount of macroeconomic-announcement precision, K_{MA} , is added into $\bar{K}_N$. Since no learning capacity has been re-allocated from the aggregate risk to firm-specific risks, the attention allocation pattern of firm-specific risks does not change. Put differently, in this case, the new allocation of attention among firm-specific risks is the same as the original allocation of attention. This extreme case more closely describes recessions when both risk aversion and aggregate volatility are high: λ_N is a monotonically increasing function in both risk aversion and aggregate volatility.

Another case may also happen when λ_N is moderately high relative to $\{\lambda_1, \dots, \lambda_{N-1}\}$. This is more likely to occur during expansions. We can better understand how to reach the new equilibrium allocation by gradually adding precision to the aggregate risk factor from any given level of K_{MA} .⁷¹ It starts from the original equilibrium allocation when λ_N is moderately high. By construction, as more precision is acquired about the aggregate risk, λ_N decreases. This process continues until λ_N reaches the second highest λ_k , $k \in \{1, \dots, N-1\}$.

Holding attention allocated to firm-specific risks constant, when λ_N reaches the second highest λ , an incremental precision allocated to the aggregate risk from K_{MA} will marginally reduce λ_N . The λ_k that was the second highest now turns to be the highest λ . Since K_{MA} cannot be allocated to firm-specific risks, any further incremental precision from K_{MA} would

⁷¹Detailed derivations of this “waterfilling equilibrium” can be found in Cover and Thomas (1991).

only further reduce λ_N , holding $\bar{K}_N^O$ constant. However, in equilibrium, $\bar{K}_N^O$ cannot be held constant. With more of K_{MA} being allocated to the aggregate risk, more of $\bar{K}_N^O$ will be re-allocated from the aggregate risk to firm- k -specific risk. If K_{MA} is large enough such that λ_N and λ_k are both reduced to equalling the originally third highest λ , then this process continues until all of K_{MA} has been used up. In this case, a strictly positive amount of learning capacity has been re-allocated from the aggregate risk to firm-specific risks. That is, in the new equilibrium, $\bar{K}_N < \bar{K}_N^O + K_{MA}$.

To sum up, when λ_N is extremely high (i.e. in recessions), no learning capacity has been re-allocated from the aggregate risk to firm-specific risks in response to a macroeconomic announcement. When λ_N is moderately high (i.e. in expansions), a strictly positive amount of learning capacity has been re-allocated from the aggregate risk to firm-specific risks in response to a macroeconomic announcement. Thus, the transient effect of macroeconomic announcements on processing firm-specific information is larger during expansions than recessions.

A.3. *Lemma 1.3 and Proposition 1.2.*

Detailed solutions to (10) can be found in Van Nieuwerburgh and Veldkamp (2010) and Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). This is a waterfilling equilibrium as comprehensively discussed in Cover and Thomas (1991). Since (10) is a linear combination of investor j 's choice variables $K_{1j}^O, \dots, K_{Nj}^O$, the “first-order condition” approach does not work here. Instead, corner solutions are suggested in Nieuwerburgh and Veldkamp (2010) and Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Essentially, it is optimal to allocate all learning capacity to the risk(s) with the highest λ , the marginal value of acquiring an incremental unit of information precision. When there are multiple risks with $\lambda = \max_l \lambda_l$, investor j would allocate all her learning capacity among these risks.

Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) assumes that the supply of the aggregate risk is way larger than ($\gg$) those of firm-specific risks such that λ_N can be either the unique $\lambda = \max_l \lambda_l$ or at least among the multiple $\lambda = \max_l \lambda_l$. Following this setup, the solutions to the optimal choices of information acquisition problem are: $K_{Nj}(\sigma_N) = K_j$, and $K_{ij}(\sigma_N) = 0$ for $i = 1, \dots, N - 1$ if λ_N is the unique $\lambda = \max_l \lambda_l$. When there are multiple $\lambda = \max_l \lambda_l$, investor j will allocate all her learning capacity K_j among these risks, including the aggregate risk.

When the aggregate volatility exogenously increases from σ_N to σ'_N by a discrete unit, there are two cases to consider following Kacperczyk, Van Nieuwerburgh and Veldkamp (2016).

- Case 1: When $\lambda_N(\sigma_N)$ is the unique $\lambda = \max_l \lambda_l$.

In this case, $\lambda_N(\sigma'_N)$ remains the unique $\lambda(\sigma'_N) = \max_l \lambda_l(\sigma'_N)$ after the aggregate volatility exogenously increases from σ_N to σ'_N because $\frac{\partial \lambda_N}{\partial \sigma_N} > 0$. Since there is no change upon the relative ranking of all λ 's, there is no change in investor j 's allocation of learning capacity when the aggregate volatility exogenously increases from σ_N to σ'_N . This pattern applies to all investors $j \in [0, 1]$. That is, in this case, $\bar{K}_i^O(\sigma'_N) = \int_0^1 K_{ij}^O(\sigma'_N) dj = \int_0^1 K_{ij}^O(\sigma_N) dj = \bar{K}_i^O(\sigma_N)$ for $i = 1, \dots, N$. Notably, in this case, $\lambda_N(\sigma'_N) > \lambda_N(\sigma_N)$, and $\lambda_i(\sigma'_N) = \lambda_i(\sigma_N)$ for $i = 1, \dots, N - 1$.

- Case 2: When $\lambda_N(\sigma_N)$ is among multiple $\lambda = \max_l \lambda_l$.

In this case, holding the allocation of learning capacity constant, $\lambda_N(\sigma'_N)$ will become the unique $\lambda(\sigma'_N) = \max_l \lambda_l(\sigma'_N)$ after the aggregate volatility exogenously increases from σ_N to σ'_N because $\frac{\partial \lambda_N}{\partial \sigma_N} > 0$. Once $\lambda_N(\sigma'_N)$ becomes the unique $\lambda(\sigma'_N) = \max_l \lambda_l(\sigma'_N)$, the learning capacity that used to be allocated firm-specific risks will now start to be re-allocated to the aggregate risk. This applies to all investors $j \in [0, 1]$. This re-allocation process will continue until (i) all learning capacity has been allocated to the aggregate risk, or (ii) $\lambda_N(\sigma'_N)$ joins the other firm-specific risks with $\lambda(\sigma'_N) = \max_l \lambda_l(\sigma'_N)$.

For investor j , $K_{Nj}^O(\sigma'_N) > K_{Nj}^O(\sigma_N)$, $K_{ij}^O(\sigma'_N) < K_{ij}^O(\sigma_N)$ for firm-specific risks that used to have $\lambda = \max_l \lambda_l$, and $K_{Nj}^O(\sigma'_N) = K_{Nj}^O(\sigma_N)$ for all other risks. Aggregating these results for all investors, we have $K_N^O(\sigma'_N) > K_N^O(\sigma_N)$, $K_i^O(\sigma'_N) < K_i^O(\sigma_N)$ for firm-specific risks that used to have $\lambda = \max_l \lambda_l$, and $K_N^O(\sigma'_N) = K_N^O(\sigma_N)$ for all other risks. Notably, in this case, $\lambda_i(\sigma'_N) > \lambda_i(\sigma_N)$ for risks with $\lambda(\sigma'_N) = \max_l \lambda_l(\sigma'_N)$, and $\lambda_i(\sigma'_N) = \lambda_i(\sigma_N)$ for all other risks.

To sum up Cases 1 and 2, we know that $\bar{K}_N^O$ weakly increases and $\bar{K}_i^O$ weakly decreases, $i = 1, \dots, N - 1$ in response to an exogenous increase in σ_N . This is Lemma 1.3.

Proposition 1.2 directly follows the proof of Lemma 1.3 regarding the two possible cases to discuss. Case 1 is essentially the “high- λ_N ” state and Case 2 the “low- λ_N ” state in a probabilistic sense. As discussed above, when $\lambda_N(\sigma_N)$ is high such that $\lambda_N(\sigma_N)$ is the unique $\lambda = \max_l \lambda_l$, there will be no change in the average learning capacity allocated to firm-specific risks in response to the exogenous increase in aggregate volatility. However, when $\lambda_N(\sigma_N)$ is low such that $\lambda_N(\sigma_N)$ is among the multiple $\lambda = \max_l \lambda_l$, there will be weakly positive changes in the average learning capacity allocated to firm-specific risks in response to the exogenous increase in aggregate volatility. This is Proposition 1.2.

Appendix B. Proofs of Chapter Two

Lemma 2.1.

Equilibrium price of firm i is conjectured to take the linear form, for $i = 1, \dots, N$:

$$p_i = \mu_1 \bar{V}_i + \mu_2 \tilde{V}_i + \mu_3 (1 + x_i) \quad (39)$$

Rescaling the price signal into:

$$\tilde{s}_i = \frac{p_i - \mu_1}{\mu_2} = \tilde{V}_i + \frac{\mu_3}{\mu_2} (1 + x_i) \quad (40)$$

Please note that p_i and $\tilde{s}_i$ contains the same information. The precision of this rescaled price signal is $\frac{\mu_2^2}{\mu_3} \gamma$. Then applying Bayesian updating to form investor j 's posterior beliefs:

$$E_j \left(\tilde{V}_i \right) = \frac{\alpha_i \bar{V}_i + \kappa(m_{ij}) \left(\tilde{V}_i + \epsilon_{ij}^\nu \right) + K'_{ij} \left(\tilde{V}_i + \epsilon_{ij}^\theta \right) + \frac{\mu_2^2}{\mu_3} \gamma \tilde{s}_i}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3} \gamma} \quad (41)$$

$$Var_j \left(\tilde{V}_i \right) = \frac{1}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3} \gamma} \quad (42)$$

Plugging (41) and (42) into (23) gives:

$$q_{ij} = \frac{1}{\rho} \left(\alpha_i \bar{V}_i + \kappa(m_{ij}) \left(\tilde{V}_i + \epsilon_{ij}^\nu \right) + K'_{ij} \left(\tilde{V}_i + \epsilon_{ij}^\theta \right) + \frac{\mu_2^2}{\mu_3} \gamma \tilde{s}_i - r p_i \left(\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3} \gamma \right) \right) \quad (43)$$

Equilibrium price of firm i can be obtained by equating demand and supply of firm i 's shares in (24):

$$\int_0^1 q_{ij} dj = 1 + x_i \quad (44)$$

Rearranging the terms delivers the equilibrium price of firm i as a linear function of $\bar{V}_i$, $\tilde{V}_i$, and x_i ⁷²:

$$p_i = \frac{\alpha_i \bar{V}_i + \left(K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma\right) \tilde{V}_i + \left(\frac{\mu_2}{\mu_3} \gamma - \rho\right) (1 + x_i)}{r \left(\alpha_i + \bar{K}_i + \frac{\mu_2^2}{\mu_3^2} \gamma\right)} \quad (45)$$

The coefficients of $\bar{V}_i$, $\tilde{V}_i$, and x_i in (45) contain μ_1 , μ_2 , and μ_3 , which can be solved by matching the coefficients in (39) and (45). Specifically,

$$\mu_1 = \frac{\alpha_i}{r \left(\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma\right)} \quad (46)$$

$$\mu_2 = \frac{\bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma}{r \left(\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma\right)} \quad (47)$$

$$\mu_3 = -\frac{\left(\frac{\bar{K}_i}{\rho} \gamma + \rho\right)}{r \left(\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma\right)} \quad (48)$$

This is Lemma 2.1.

Lemma 2.2, Lemma 2.3 and Properties 1-3

Solutions to stage 2 and stage 3 problems are readily established in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). For investor j choosing K_{ij} , the objective function to maximize is

$$\sum_{i=1}^N \lambda_i K_{ij} + \text{constant} \quad (49)$$

⁷²One useful result to mention is $\int_0^1 IR_{ij} \epsilon_{ij}^\theta dj = \int_0^1 IR_{ij} dj \int_0^1 \epsilon_{ij}^\theta dj = 0$. This is due to the fact that IR_{ij} and ϵ_{ij}^θ are linearly uncorrelated. Similarly, we have $\int_0^1 \kappa(m_{ij}) \epsilon_{ij}^\nu dj = \int_0^1 \kappa(m_{ij}) dj \int_0^1 \epsilon_{ij}^\nu dj = 0$.

subject to the constraints (19) and (20), which can be rewritten as:

$$\sum_{i=1}^N IR_{ij} \leq K_j - \sum_{i=1}^N \kappa(m_{ij}) \quad (50)$$

$$IR_{ij} \geq 0 \quad (51)$$

where $IR_{ij} = K_{ij} - \kappa(m_{ij})$. Since b_{ij} 's are monitoring effort readily chosen in stage 1, the maximization problem above regards all b_{ij} 's and thus all $\kappa(m_{ij})$'s as constant; the objective function can also be rewritten as:

$$\sum_{i=1}^N \lambda_i IR_{ij} + \sum_{i=1}^N \lambda_i \kappa(m_{ij}) + \text{constant} \quad (52)$$

Therefore, the original optimization problem is equivalent to maximizing (52) subject to the constraints (50) and (51). With the rewritten objective function and constraints, we can apply the solutions in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Since λ_i , as indicated in (27), is composed of aggregate variables and each investor in this model is atomic on a continuum of mass one, investor j regards λ_i as a constant when making choices of K_{ij} . Further, all investors face the same λ_i 's for $i = 1, \dots, N$ in their own optimization problem. Van Nieuwerburgh and Veldkamp (2010) also formally prove that the solution of such optimization problem when there is a unique $\lambda_i = \max_l \lambda_l$ is: $IR_{ij} = K_j - \sum_{i=1}^N \kappa(m_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $IR_{ij} = 0$ otherwise. That is, $K_{ij} = (K_j - \sum_{i=1}^N \kappa(b_{ij})) + \kappa(m_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $K_{ij} = \kappa(m_{ij})$ otherwise.

Naturally, we cannot rule out the possibility that there may be multiple firms with the same level of $\lambda = \max_l \lambda_l$. This can happen when K_j is large enough. In this situation, investor j will be indifferent to allocating $K_j - \sum_{i=1}^N \kappa(m_{ij})$, her remaining capacity after

monitoring, to the firms with the same level of $\lambda = \max_l \lambda_l$. For simplicity, we may assume that equal fractions of her remaining capacity are allocated to each firm with $\lambda = \max_l \lambda_l$. That is, $K_{ij} = \frac{1}{n} (K_j - \sum_{i=1}^N \kappa(m_{ij})) + \kappa(m_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $K_{ij} = \kappa(m_{ij})$ otherwise, where n is the number of firms with $\lambda = \max_l \lambda_l$. Overall, K_{ij} , information acquisition of firm i by investor j , is weakly increasing in monitoring effort of the same firm, m_{ij} . The cross-firm relation between information acquisition and monitoring is that K_{ij} is weakly decreasing in m_{kj} where $i \neq k$. This is Lemma 2.2.

After solving the stage 2 and stage 3 problems in this model, we can use backward induction to work on the stage 1 problem: optimally choose m_{ij} . The stage 1 utility of investor j takes the following form:

$$U_{1j} = r \left(\sum_{i=1}^N (\beta_{ij} \bar{V}_i - m_{ij}) \right) + \sum_{i=1}^N \lambda_i K_{ij} + \text{constant} \quad (53)$$

For firms with $\lambda_i \neq \max_l \lambda_l$, assuming interior solutions and setting the FOC w.r.t. b_{ij} equal to zero gives:

$$\frac{\partial U_{1j}}{\partial m_{ij}} = r \left(\beta_{ij} \phi_i \frac{1}{1 + m_{ij}} - 1 \right) + (\lambda_i - \max_l \lambda_l) \phi_m \frac{1}{1 + m_{ij}} = 0 \quad (54)$$

Rearranging terms in (34) gives:

$$m_{ij} = \beta_{ij} \phi_i + \frac{(\lambda_i - \max_l \lambda_l) \phi_m}{r} - 1 \quad (55)$$

For firms with multiple $\lambda_i = \max_l \lambda_l$, assuming interior solutions and setting the FOC w.r.t. b_{ij} equal to zero gives:

$$\frac{\partial U_{1j}}{\partial b_{ij}} = r \left(\beta_{ij} \phi_i \frac{1}{1 + m_{ij}} - 1 \right) + \lambda_i \frac{(n-1) \phi_m}{n} \frac{1}{1 + m_{ij}} = 0 \quad (56)$$

where n is the number of multiple firms with the highest λ_i . Rearranging terms in (56) gives:

$$b_{ij} = \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1 \quad (57)$$

(57) can also accommodate the case that investor j has one and only one firm with $\lambda_i = \max_l \lambda_l$ by setting $n = 1$. To sum up, according to $m_{ij} \geq 0$, the optimal monitoring effort can be expressed as

$$m_{ij}^* = \begin{cases} \max\{0, \beta_{ij}\phi_i + \frac{(\lambda_i - \max_l \lambda_l)\phi_m}{r} - 1\} & \lambda_i \neq \max_l \lambda_l \\ \max\{0, \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1\} & \lambda_i = \max_l \lambda_l \end{cases}$$

Here is Lemma 2.3. There are a few properties associated with this lemma.

Property 1 If assuming interior solution, differentiating m_{ij}^* w.r.t. β_{ij} gives

$$\frac{\partial m_{ij}^*}{\partial \beta_{ij}} = \phi_i > 0 \quad (58)$$

Taking into account the possible corner solution $m_{ij}^* = 0$, it is claimed that m_{ij} is weakly increasing in β_{ij} .

Property 2 If assuming interior solution, differentiating m_{ij}^* w.r.t. ϕ_i gives

$$\frac{\partial m_{ij}^*}{\partial \phi_i} = \beta_{ij} > 0 \quad (59)$$

Taking into account the possible corner solution $m_{ij}^* = 0$, it is claimed that m_{ij} is weakly increasing in ϕ_i .

Property 3 This property can be derived using the chain rule. Assuming interior solution,

$\frac{\partial m_{ij}^*}{\partial \lambda_i} \geq 0$ is straightforward from Lemma 2. Using the chain rule and given that $\frac{\partial \lambda_i}{\partial \sigma_i} =$

$(1 + 2\bar{\sigma}_i (\rho^2 (\sigma_x + 1) + \bar{K}_i)) \left(\frac{\bar{\sigma}_i}{\sigma_i} \right)^2 > 0$, we can claim that m_{ij}^* is weakly increasing in σ_i via λ_i . This is also true after considering the possible corner solution.

Proposition 2.1.

Were there no link between monitoring and information acquisition, investor j 's monitoring decision would only depend on the stage 1 problem: maximize her initial wealth after monitoring $W_0 = \sum_{i=1}^n (\beta_{ij} \bar{V}_i - m_{ij})$. Assuming interior solution, taking the first order derivative w.r.t. m_{ij} gives:

$$\beta_{ij} \phi_i \frac{1}{1 + m_{ij}} - 1 = 0 \quad (60)$$

That is,

$$m_{ij} = \beta_{ij} \phi_i - 1 \quad (61)$$

Considering $m_{ij} \geq 0$, optimal monitoring effort in this situation is

$$m_{ij}^{BM} = \max\{0, \beta_{ij} \phi_i - 1\} \quad (62)$$

where m_{ij}^{BM} denote this benchmark-case allocation of monitoring effort. Please note that this is a variant of the basic model but with $\phi_m = 0$. Comparing m_{ij}^* and m_{ij}^{BM} , there are several cases to consider as follows.

Case 1: For firms with $\lambda_i \neq \max_l \lambda_l$,

- If $\beta_{ij} \phi_i + \frac{(\lambda_i - \max_l \lambda_l) \phi_m}{r} > 1$, then $m_{ij}^* = \beta_{ij} \phi_i + \frac{(\lambda_i - \max_l \lambda_l) \phi_m}{r} - 1$ and $m_{ij}^{BM} = \beta_{ij} \phi_i - 1$; that is, $m_{ij}^* - m_{ij}^{BM} = \frac{(\lambda_i - \max_l \lambda_l) \phi_m}{r} < 0$.
- If $\beta_{ij} \phi_i + \frac{(\lambda_i - \max_l \lambda_l) \phi_m}{r} \leq 1 < \beta_{ij} \phi_i$, then $m_{ij}^* = 0$ and $m_{ij}^{BM} = \beta_{ij} \phi_i - 1 > 0$; that is, $m_{ij}^* - m_{ij}^{BM} < 0$.

- If $\beta_{ij}\phi_i \leq 1$, then $m_{ij}^* = 0$ and $b_{ij}^{BM} = 0$; that is, $m_{ij}^* - m_{ij}^{BM} = 0$.

To sum up Case 1, $m_{ij}^* \leq m_{ij}^{BM}$ for firms with $\lambda_i \neq \max_l \lambda_l$.

Case 2: For firms with $\lambda_i = \max_l \lambda_l$,

- If $\beta_{ij}\phi_i > 1$, then $m_{ij}^* = \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1$ and $m_{ij}^{BM} = \beta_{ij}\phi_i - 1$; that is, $m_{ij}^* - m_{ij}^{BM} = \frac{(n-1)\lambda_i\phi_m}{nr} \geq 0$.
- If $\beta_{ij}\phi_i \leq 1 < \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr}$, then $m_{ij}^* = \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1 > 0$ and $m_{ij}^{BM} = 0$; that is, $m_{ij}^* - m_{ij}^{BM} > 0$.
- If $\beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} \leq 1$, then $m_{ij}^* = 0$ and $m_{ij}^{BM} = 0$; that is, $m_{ij}^* - m_{ij}^{BM} = 0$.

To sum up Case 2, $m_{ij}^* \geq m_{ij}^{BM}$ for firms with $\lambda_i = \max_l \lambda_l$. Clearly, comparing the results in Case 1 and Case 2, we can find that there is a re-allocation pattern of monitoring effort relative to the benchmark case: Monitoring effort is re-allocated to firms with $\lambda_i = \max_l \lambda_l$ from firms with $\lambda_i \neq \max_l \lambda_l$.

Propositions 2.2 and 2.3.

One useful and important feature is that since IR_{ij} is determined by λ_i and other given parameters, variations in m_{ij} or β_{ij} will not change λ_i . Therefore, variations in m_{ij} or β_{ij} will not change IR_{ij} , either. Specifically, when taking partial derivative of K_{ij} w.r.t. m_{ij} , $\frac{\partial K_{ij}}{\partial m_{ij}} = \frac{\phi_m^i}{1+m_{ij}} \geq 0$, where $\phi_m^i = \phi_m$ for firms with $\lambda_i \neq \max_l \lambda_l$; $\phi_m^i = \frac{(n-1)\phi_m}{n}$ for multiple firms with $\lambda_i = \max_l \lambda_l$; and $\phi_m^i = 0$ if there is one and only one firm with $\lambda_i = \max_l \lambda_l$. Based on the first two properties of optimal monitoring effort solved in Appendix B, we may get:

$$\frac{\partial K_{ij}}{\partial \beta_{ij}} = \frac{\partial K_{ij}}{\partial m_{ij}} \frac{\partial m_{ij}}{\partial \beta_{ij}} \geq 0 \quad (63)$$

where both $\frac{\partial K_{ij}}{\partial m_{ij}}$ and $\frac{\partial m_{ij}}{\partial \beta_{ij}}$ are weakly positive. Similary,

$$\frac{\partial K_{ij}}{\partial \phi_i} = \frac{\partial K_{ij}}{\partial m_{ij}} \frac{\partial m_{ij}}{\partial \phi_i} \geq 0 \quad (64)$$

where both $\frac{\partial K_{ij}}{\partial m_{ij}}$ and $\frac{\partial m_{ij}}{\partial \phi_i}$ are weakly positive.

Proposition 2.4a. Marginal Shock to Prior Uncertainty

According to Lemma 2.2, there are two cases to consider when exploring how m_{ij}^* responds to an exogenous marginal increase in σ_k ($k \neq i$).

Case 1: For firms with $\lambda_i \neq \max_l \lambda_l$, $m_{ij}^* = \max\{0, \beta_{ij}\phi_i + \frac{(\lambda_i - \max_l \lambda_l)\phi_m}{r} - 1\}$; an exogenous increase in σ_k ($k \neq i$) weakly increases $\max_l \lambda_l$ and thus weakly decreases m_{ij}^* .

Case 2: For firms with $\lambda_i = \max_l \lambda_l$, $m_{ij}^* = \max\{0, \beta_{ij}\phi_i + \frac{(n-1)\lambda_i\phi_m}{nr} - 1\}$; there are two situations to consider regarding an exogenous marginal increase in σ_k ($k \neq i$).

- If $\lambda_k < \lambda = \max_l \lambda_l$ before the exogenous increase in σ_k happens, then $\lambda_k < \lambda = \max_l \lambda_l$ still holds after that exogenous increase. This is because an exogenous marginal increase in σ_k only increases λ_k marginally while $\lambda_k < \lambda = \max_l \lambda_l$ in a discrete manner. In this situation, m_{ij}^* with $\lambda_i = \max_l \lambda_l$ is not affected.
- If λ_k is one of the multiple $\lambda = \max_l \lambda_l$, then λ_k becomes the unique $\lambda = \max_l \lambda_l$ after this exogenous increase, holding attention allocation constant. However, this exogenous increase in σ_k affects all investors and the λ 's as well. When all investors allocate more attention (for information acquisition) to firm k in response to this exogenous marginal increase in σ_k , λ_k starts facing downward pressure.⁷³ This is because when all investors acquire more information about the same firm, the value of obtaining an incremental unit of information precision about this firm will decrease.

Grossman and Stiglitz (1980) recognize this strategic substitutability of information

⁷³Cover and Thomas (1991) provide a “waterfilling” solution to this type of question in information theory.

acquisition. Such attention re-allocation to firm k continues until firm k joins the other firms having $\lambda = \max_l \lambda_l$ in the new equilibrium. Specifically, λ_k in the new equilibrium is marginally bigger than before, so are all the other λ 's since $\lambda_k = \lambda = \max_l \lambda_l$ holds in the new equilibrium. From Lemma 2, we can see that monitoring effort m_{ij}^* increases among firms with $\lambda_i = \max_l \lambda_l$ via the associated increase in λ_i .

To sum up, in the new equilibrium, m_{ij}^* weakly decreases in response to an exogenous marginal increase in σ_k ($k \neq i$) if $\lambda_i \neq \max_l \lambda_l$; nonetheless, m_{ij}^* strictly increases in response to an exogenous marginal increase in σ_k ($k \neq i$) if $\lambda_i = \max_l \lambda_l$.

Proposition 2.4b. Large Shock to Prior Uncertainty

When the exogenous increase in σ_k is large enough such that λ_k becomes the unique $\max_l \lambda_l$ ex post, then from Lemma 2.3, it is clear that m_{ij} weakly decreases for any $i \neq k$.

B.1. Informational Advantage from Monitoring

To model the private information acquired during the process of monitoring as an informational advantage, there are a few changes that need to be clarified. First, $\kappa(m_{ij})$ can no longer be *directly* used to form portfolio choices. That is, without conducting any independent research about firm i , making effort to monitoring firm i does not reduce investor j 's uncertainty about firm i . Second, $K_{ij} = IR_{ij}$, the signal precision of private information acquired via independent research in stage 2. That is, the only source of private information that can be applied to portfolio choice decisions is the private information acquired via independent research. The relative costliness of conducting independent research about a firm depends on how much monitoring effort has been made about this firm. Specifically, informational advantage $\kappa(m_{ij})$ can be incorporated into the information processing capacity

constraint as follows:

$$\sum_{i=1}^N \frac{K_{ij}}{\kappa(m_{ij})} \leq K_j \quad (65)$$

where the scaling factor $\frac{1}{\kappa(m_{ij})}$ measures the relative cost of information acquisition across firms. This modified constraint allows conducting independent research about different firms to be differentially costly, and the relative costliness depends on investors' monitoring activities. If investor j chooses to make more effort to monitor firm i in stage 1, then she will rationally expect it less costly to acquire information about this firm via independent research in stage 2. For simplicity, $\kappa(m_{ij})$ can take the functional form: $\kappa(m_{ij}) = 1 + \phi_m \ln(1 + m_{ij})$.

The original optimization problem at stage 2 in the main text is to be rewritten as:

$$\begin{aligned} & \max_{K_{ij}} \sum_{i=1}^N \lambda_i K_{ij} + \text{constant} \\ &= \max_{K_{ij}} \sum_{i=1}^N \lambda_i \kappa(m_{ij}) \frac{K_{ij}}{\kappa(m_{ij})} + \text{constant} \end{aligned} \quad (66)$$

subject to $\sum_{i=1}^N \frac{K_{ij}}{\kappa(m_{ij})} \leq K_j$ and $K_{ij} \geq 0$. Define $\bar{K}_{ij} = \frac{K_{ij}}{\kappa(m_{ij})}$; solutions to $\bar{K}_{ij}$ in stage 2 problem are equivalent to solutions to K_{ij} because $\kappa(m_{ij})$ is a deterministic function of monitoring effort b_{ij} , a choice variable that has been determined in stage 1. Define $\bar{\lambda}_{ij} = \lambda_i \kappa(m_{ij})$, and now $\bar{\lambda}_{ij}$ reflects the relative importance for investor j to acquire private information about firm i among all n firms. Investor j 's individual choice of m_{ij} cannot change λ_i but can change $\bar{\lambda}_{ij}$ via $\kappa(m_{ij})$. Plugging in the new terms, the optimization problem is now:

$$\max_{\bar{K}_{ij}} \sum_{i=1}^N \bar{\lambda}_{ij} \bar{K}_{ij} + \text{constant} \quad (67)$$

subject to the information processing constraint

$$\sum_{i=1}^N \bar{K}_{ij} \leq K_j \quad (68)$$

and the no-forgetting constraint

$$\bar{K}_{ij} \geq 0 \quad (69)$$

for $i = 1, 2, \dots, N$. As before, since investor j is one of the continuum of investors with mass one, her individual action will not change “aggregate variables”, and therefore m_{ij} and K_{ij} will not change λ_i . Monitoring choice m_{ij} is already determined in stage 1 and can be considered as a constant in stage 2. Now, the solution takes the new form: $\bar{K}_{ij} = K_j$ if $\bar{\lambda}_{ij} = \max_l \bar{\lambda}_{lj}$ and $\bar{K}_{ij} = 0$ otherwise. When there are multiple firms with the same level of $\bar{\lambda}_j = \max_l \bar{\lambda}_{lj}$, investor j will be indifferent to allocating her capacity K_j to the firms with the same level of $\bar{\lambda}_j = \max_l \bar{\lambda}_{lj}$.

For simplicity, again, we assume that that equal fractions of her remaining capacity are allocated to each firm with $\bar{\lambda}_j = \max_l \bar{\lambda}_{lj}$. Let $K_{ij}^{**}(m_{ij})$ denote the optimal choice of K_{ij} given investor j ’s monitoring effort m_{ij} . Then, $K_{ij}^{**}(m_{ij}) = \phi_m^i \kappa(m_{ij})$, where $\phi_m^i = 0$ for firms with $\bar{\lambda}_{ij} \neq \max_l \bar{\lambda}_{lj}$; $\phi_m^i = \frac{\phi_m}{n} K_j$ for firms with multiple $\bar{\lambda}_{ij} = \max_l \bar{\lambda}_{lj}$; and $\phi_m^i = \phi_m K_j$ if investor j has one and only one firm with $\bar{\lambda}_{ij} = \max_l \bar{\lambda}_{lj}$. The within-firm complementarity between monitoring and information acquisition in Lemma 2.2 is straightforward: $\frac{\partial K_{ij}^{**}}{\partial m_{ij}} \geq 0$. The cross-firm substitutability between monitoring and information acquisition can be obtained as follows. Given an exogenous increase in m_{kj} , λ_k is unchanged but $\bar{\lambda}_{kj} = \lambda_k \kappa(m_{kj})$ is increased. Since in this setup $\bar{\lambda}_{kj}$ determines the relative importance of acquiring information, an exogenous increase in m_{kj} will weakly increase K_{kj} and crowds out K_{ij} , ($i \neq k$).

After solving for optimal information acquisition, we still need to go back to stage 1 and solve the problem of optimal monitoring.

$$U_{1j} = r \left[\sum_{i=1}^N (\beta_{ij} \bar{V}_i - m_{ij}) \right] + \sum_{i=1}^N \lambda_i K_{ij}^{**}(m_{ij}) + \text{constant} \quad (70)$$

Assuming interior solutions and differentiating (70) w.r.t. m_{ij} gives the FOC as:

$$\frac{\partial U_{1j}}{\partial m_{ij}} = r \left(\beta_{ij} \phi_i \frac{1}{1 + m_{ij}} - 1 \right) + \lambda_i \phi_m^i \frac{1}{1 + m_{ij}} = 0 \quad (71)$$

resulting in a similar equation with Lemma 2.2 after considering the possible corner solution:

$$m_{ij}^* = \max \left\{ 0, \beta_{ij} \phi_i + \frac{\lambda_i \phi_m^i}{r} - 1 \right\} \quad (72)$$

From this expression, clearly, it is easy to find that optimal monitoring effort is weakly increasing in engagement effectiveness, ϕ_i , and initial holdings, β_{ij} . Besides, m_{ij}^* is weakly increasing in σ_i via λ_i . In this setup, the term $\frac{\lambda_i \phi_m^i}{r}$ represents the re-allocation pattern of optimal monitoring effort if compared to the baseline case. That is, $m_{ij}^* - m_{ij}^{**} = \max \left\{ 0, \frac{\lambda_i \phi_m^i}{r} \right\} \geq 0$. This is consistent with Proposition 2.1 and its properties.⁷⁴ Following the chain rule, $K_{ij}^{**} = \frac{\phi_m^i}{\phi_m} \kappa(m_{ij})$ is weakly increasing in engagement effectiveness, ϕ_i , and initial holding, β_{ij} . Therefore, Propositions 2.2 and 2.3 still hold.

In response to an exogenous marginal increase in σ_k , ($k \neq i$), m_{ij} is not affected for firms with $\bar{\lambda}_{ij} \neq \max_l \bar{\lambda}_{lj}$; m_{ij} is weakly increased for firms with $\bar{\lambda}_{ij} = \max_l \bar{\lambda}_{lj}$. This is consistent with how m_{ij} behaves in Proposition 2.4a.

⁷⁴Since the piece of private information acquired during the process of monitoring does not directly occupy learning capacity, therefore we do not observe “re-allocated” monitoring attention from low- λ_i firms to high- λ_i firms. But in relative terms cross-sectionally, we can still reserve the “monitoring-for-learning” feature in the sense that monitoring attention is allocated more to firms with high- λ_i firms.

When the exogenous increase in σ_k is large enough such that $\bar{\lambda}_{ij}$ becomes the unique $\max_i \bar{\lambda}_{ij}$ ex post, both λ_i and ϕ_m^i decrease. Thus, from Lemma 2.3, we can see that m_{ij} weakly decreases for all $i \neq k$. This is consistent with how m_{ij} behaves in Proposition 2.4b.

B.2. Entropy Learning Capacity

This subsection considers the entropy learning capacity constraint and the associated no-forgetting constraint as follows. Let $\kappa(m_{ij})$ still denote the firm-specific private information acquired due to investor j exerting monitoring effort on firm i such that the scaling factor $\frac{1}{\kappa(m_{ij})}$ still measures the relative costliness of information acquisition across firms, and let K_{ij} denote the signal precision of acquired private information in stage 2. Now, the entropy learning constraint takes the following form:

$$\prod_{i=1}^N \frac{K_{ij}}{\kappa(m_{ij})} \leq K_j \quad (73)$$

and the associated no-forgetting constraint takes the form:

$$K_{ij} \geq \kappa(m_{ij}) \quad (74)$$

For simplicity, $\kappa(m_{ij})$ can still take the functional form $\kappa(m_{ij}) = 1 + \phi_m \ln(1 + m_{ij})$ as before.

This appendix provides the solution to the 3-stage model with entropy learning capacity. Define $\bar{K}_{ij} = \frac{K_{ij}}{\kappa(m_{ij})}$; solutions to $\bar{K}_{ij}$ in stage 2 problem are equivalent to solutions to K_{ij} because $\kappa(m_{ij})$ is a deterministic function of monitoring effort m_{ij} , a choice variable that has been determined in stage 1. The associated entropy constraint and the no-forgetting constraint can be rewritten as $\prod_{i=1}^N \bar{K}_{ij} \leq K_j$ and $\bar{K}_{ij} \geq 1$. Define $\bar{\lambda}_{ij} = \lambda_i \kappa(m_{ij})$, and now $\bar{\lambda}_{ij}$ reflects the relative importance for investor j to acquire private information about firm i among all N firms.

Using backward induction, the portfolio choice problem in stage 3 is the same as before and Lemma 1 holds as well. Now, the solution to the information acquisition problem in stage 2 takes a similar form: $\bar{K}_{ij} = K_j$ if $\bar{\lambda}_{ij} = \max_l \bar{\lambda}_{lj}$ and $\bar{K}_{ij} = 1$ otherwise. When there are multiple firms with the same level of $\bar{\lambda} = \max_l \bar{\lambda}_{lj}$, investor j will be indifferent to allocating her capacity K_j to the firms with the same level of $\bar{\lambda} = \max_l \bar{\lambda}_{lj}$. For simplicity, we assume that geometrically equal fractions of her remaining capacity are allocated to each firm with $\bar{\lambda} = \max_l \bar{\lambda}_{lj}$. If n denotes the number of multiple firms having $\bar{\lambda} = \max_l \bar{\lambda}_{lj}$, then “geometrically equally” sharing investor j ’s learning capacity K_j refers to allocating $(K_j)^{\frac{1}{n}}$ attention to firm i using the entropy constraint. Following similar reasonings in Appendix B.1, complementarity and substitutability between monitoring and information acquisition still holds as in Lemma 2.2. Let $K_{ij}^{***}(b_{ij})$ denote the optimal choice of K_{ij} given investor j ’s monitoring effort b_{ij} in this subsection.

$$U_{1j} = r \left[\sum_{i=1}^N (\beta_{ij} \bar{V}_i - m_{ij}) \right] + \sum_{i=1}^N \lambda_i K_{ij}^{***}(m_{ij}) + \text{constant} \quad (75)$$

Assuming interior solutions and differentiating (75) w.r.t. m_{ij} gives the FOC as:

$$\frac{\partial U_{1j}}{\partial m_{ij}} = r \left(\beta_{ij} \phi_i \frac{1}{1 + m_{ij}} - 1 \right) + \lambda_i \phi_m^i \frac{1}{1 + m_{ij}} = 0 \quad (76)$$

resulting in a similar equation with Lemma 2.2 after considering the possible corner solution:

$$m_{ij}^* = \max \left\{ 0, \beta_{ij} \phi_i + \frac{\lambda_i \phi_m^i}{r} - 1 \right\} \quad (77)$$

where $\phi_m^i = \phi_m(K_j)^0$ for firms with $\bar{\lambda}_i \neq \max_l \bar{\lambda}_{lj}$; $\phi_m^i = \phi_m(K_j)^{\frac{1}{n}}$ for multiple firms with $\bar{\lambda}_i = \max_l \bar{\lambda}_{lj}$; and $\phi_m^i = \phi_m K_j$ if investor j has one and only one firm with $\bar{\lambda}_i = \max_l \bar{\lambda}_{lj}$. From this expression, we can find that optimal monitoring effort is weakly increasing in engagement effectiveness, ϕ_i , and initial holding, β_{ij} . m_{ij}^* is also weakly increasing in σ_i via λ_i . Similarly, in relative terms cross-sectionally, we can still reserve the feature that monitoring

attention is allocated more to firms with high- λ_i firms. That is, $m_{ij}^* - m_{ij}^{**} = \max \left\{ 0, \frac{\lambda_i \phi_m^i}{r} \right\} \geq 0$. This is broadly consistent with Proposition 1 and its properties. Following the chain rule, $K_{ij}^{***} = \frac{\phi_k^i}{\phi_k} \kappa(m_{ij})$ is weakly increasing in engagement effectiveness, ϕ_i , and initial holding, β_{ij} ; and therefore, Propositions 2.2 and 2.3 still hold. Propositions 2.4a and 2.4b can be obtained through similar reasonings as in Appendix B.1.

B.3. Motivation for Stock Picking Ability

The theoretical counterpart of the empirical measure

$$StockPickingAbility_{gt} = \frac{1}{N_{gt}} \sum (\Delta q_t / q_{t-1}) * SUE_{t+1}$$

is $E \left[\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right) \tilde{z}_i \right]$, where $\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right)$ is the theoretical counterpart for $(\Delta q_t / q_{t-1})$, and $\tilde{z}_i$ for SUE_{t+1} . This section shows that $E \left[\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right) \tilde{z}_i \right]$ is actually an increasing function in K_{ij} . Here is a brief derivation as follows. The ex-post holding in firm i by investor j is:

$$\begin{aligned} q_{ij} &= \frac{E_j(\tilde{V}_i) - rp_i}{Var_j(\tilde{V}_i)} \\ &= \alpha_i \bar{V}_i + \kappa(m_{ij}) (\tilde{V}_i + \epsilon_{ij}^\nu) + K'_{ij} (\tilde{V}_i + \epsilon_{ij}^\theta) + \frac{\bar{K}_i^2}{\rho^2} \gamma \tilde{V}_i - \frac{\rho}{\bar{K}_i} \gamma^{\frac{1}{2}} (1 + \tilde{x}_i) \\ &\quad - \left[\alpha_i \bar{V}_i + \left(\bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma \right) \tilde{V}_i - \left(\frac{\bar{K}_i}{\rho} \gamma + \rho \right) (1 + \tilde{x}_i) \right] \\ &= (K_{ij} - \bar{K}_i) \tilde{V}_i + \kappa(m_{ij}) \epsilon_{ij}^\nu + K'_{ij} \epsilon_{ij}^\theta + a(1 + \tilde{x}_i) \end{aligned}$$

where a is a constant. Then,

$$\begin{aligned} &E \left[\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right) \tilde{z}_i \right] \\ &= \frac{1}{\beta_{ij}} E(q_{ij} \tilde{z}_i) - 0 \\ &= \frac{1}{\beta_{ij}} E \left[\left((K_{ij} - \bar{K}_i) \tilde{V}_i + \kappa(m_{ij}) \epsilon_{ij}^\nu + K'_{ij} \epsilon_{ij}^\theta + a(1 + \tilde{x}_i) \right) \tilde{z}_i \right] \end{aligned}$$

Recall $E(\epsilon_{ij}^\nu \tilde{z}_i) = 0$, $E(\epsilon_{ij}^\theta \tilde{z}_i) = 0$, and $E(\tilde{x}_i \tilde{z}_i) = 0$. Therefore, we have

$$\begin{aligned}
& E \left[\left(\frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \right) \tilde{z}_i \right] \\
&= \frac{1}{\beta_{ij}} E \left[(K_{ij} - \bar{K}_i) \tilde{V}_i \tilde{z}_i \right] \\
&= \frac{1}{\beta_{ij}} E \left[(K_{ij} - \bar{K}_i) (\bar{V}_i + \tilde{z}_i) \tilde{z}_i \right] \\
&= 0 + \frac{1}{\beta_{ij}} E \left[(K_{ij} - \bar{K}_i) \tilde{z}_i^2 \right] \\
&= \frac{(K_{ij} - \bar{K}_i)}{\beta_{ij}} E(\tilde{z}_i^2) \\
&= \frac{\sigma_i (K_{ij} - \bar{K}_i)}{\beta_{ij}}
\end{aligned}$$

which is an increasing function in K_{ij} . That is, the more precise information investor j has about firm i , the more positively correlated the way she adjusts her holdings in firm i will be with firm i 's next-period earnings surprises.

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Figure 1.1. Implied Volatility of S&P 100 Index Option

This figure presents the timing relation of implied volatility of S&P 100 with the releases of macroeconomic announcements. *Macroday* equals 1 if a macroeconomic announcement is scheduled on time t . The vertical axis measures the level of implied volatility relative to day *Macroday*. The horizontal axis is the relative timing with 10 days before and 10 days after *Macroday*. The level of implied volatility on *Macroday* is linearly scaled to zero for easier illustration. *** and ** represent statistical significance at the 1% and 5% level, respectively.

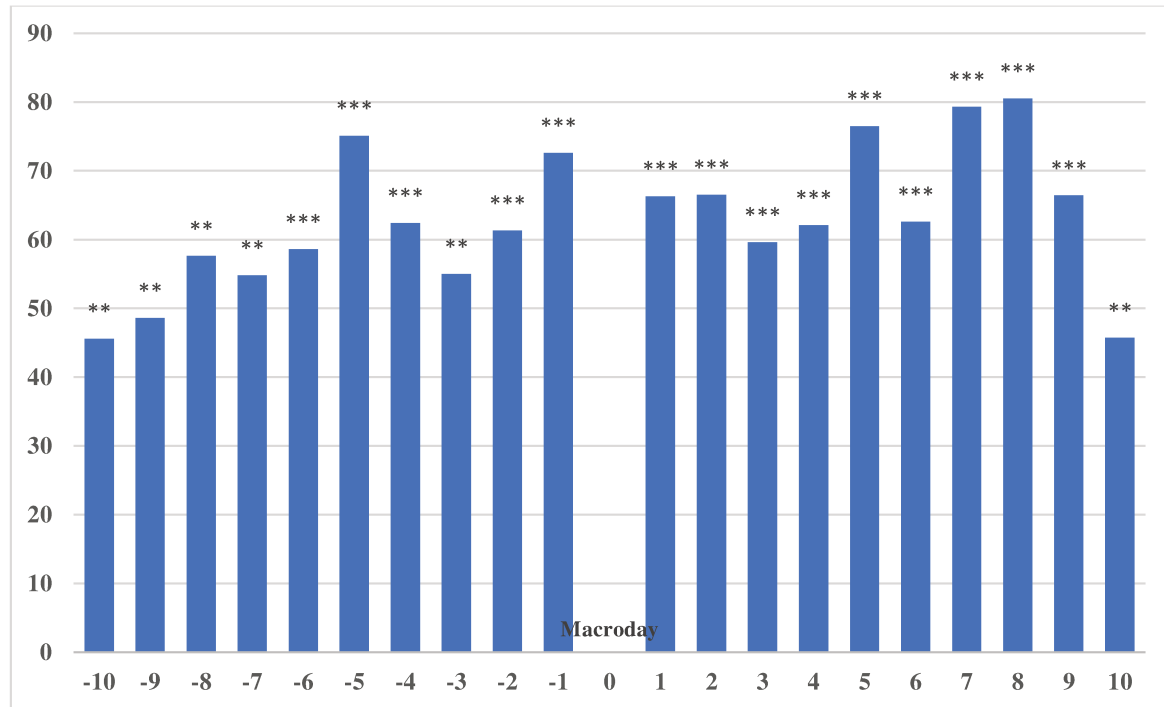


Figure 1.2. Timeline for Empirical Settings

This figure shows the timeline for the empirical settings in this paper. A firm's quarterly earnings announcement takes place at time 0. In the main results, immediate price response to earnings announcements is measured by $CAR(0,1)$ and delayed response to earnings announcements by $CAR(2,15)$. The whole pre-earnings-announcement drift is measured by $CAR(-15,-1)$. $CAR(-15,-1)$ is further decomposed into response to analyst earnings forecast consensus (REF) and investor private information (InvestorPI), which are respectively captured by $CAR(-15, ecd)$ and $CAR(ecd+1,-1)$, where ecd is the date of forming earnings consensus for a firm by I/B/E/S.

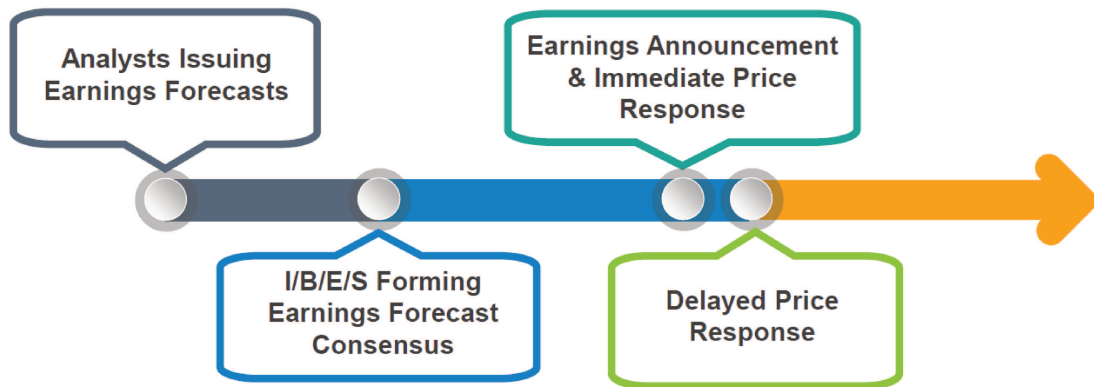


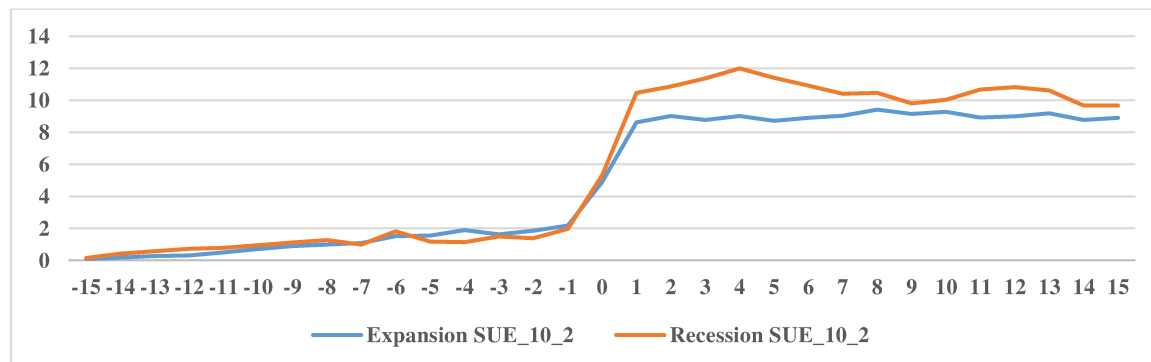
Figure 1.3. Heterogeneity in Immediate Price Responses, Expansions and Recessions

This table presents the heterogeneity in dispersions of Fama-French 3-factor $CAR(0,1)$ during expansions and recessions, respectively. The vertical axis is $CAR(-15,t)$, the cumulative abnormal return starting from 15 days before a firm's earnings announcement. The horizontal axis is the number of days relative to a firm's earnings announcement date ($t=0$). Following Dellavignall and Pollet (2009), SUE is the 11 quantiles of standardized unexpected earnings where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. Panel A shows the difference in median $CAR(-15,t)$ between $SUE=11$ and $SUE=1$, Panel B between $SUE=10$ and $SUE=2$, and Panel C between $SUE=9$ and $SUE=3$.

Panel A. Difference in median $CAR(-15,t)$ between $SUE=11$ and $SUE=1$



Panel B. Difference in median $CAR(-15,t)$ between $SUE=10$ and $SUE=2$



Panel C. Difference in median $CAR(-15,t)$ between $SUE=9$ and $SUE=3$

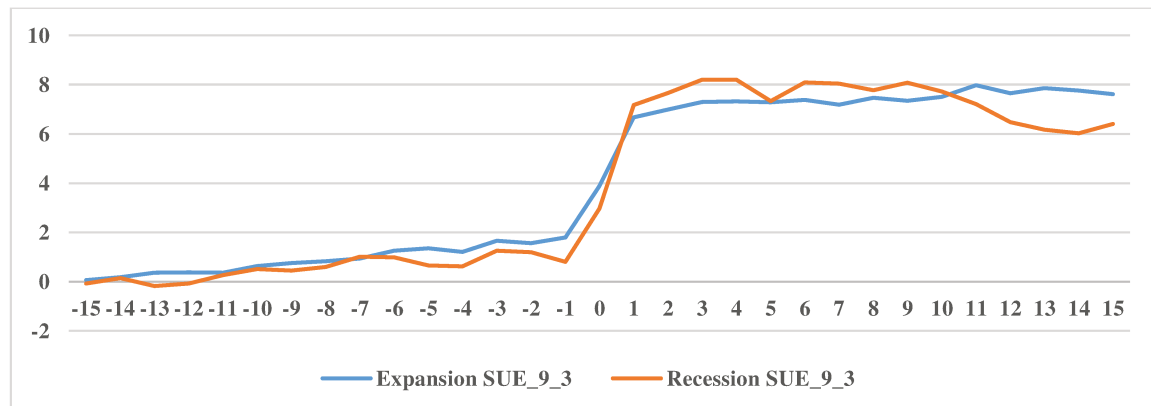


Figure 1.4. Abnormal Trading Volume around Earnings Announcements

This figure compares the abnormal trading volume around firm-earnings news announced on *Macroday* with that on *Non-Macroday*. The vertical axis is abnormal trading volume defined as in Hershleifer, Lim and Teoh (2009). The horizontal axis is relative timing around firm earnings announcement. Absolute earnings surprises are sorted into quintiles. This figure shows the comparison with “absolute earnings surprise quintile=3”.

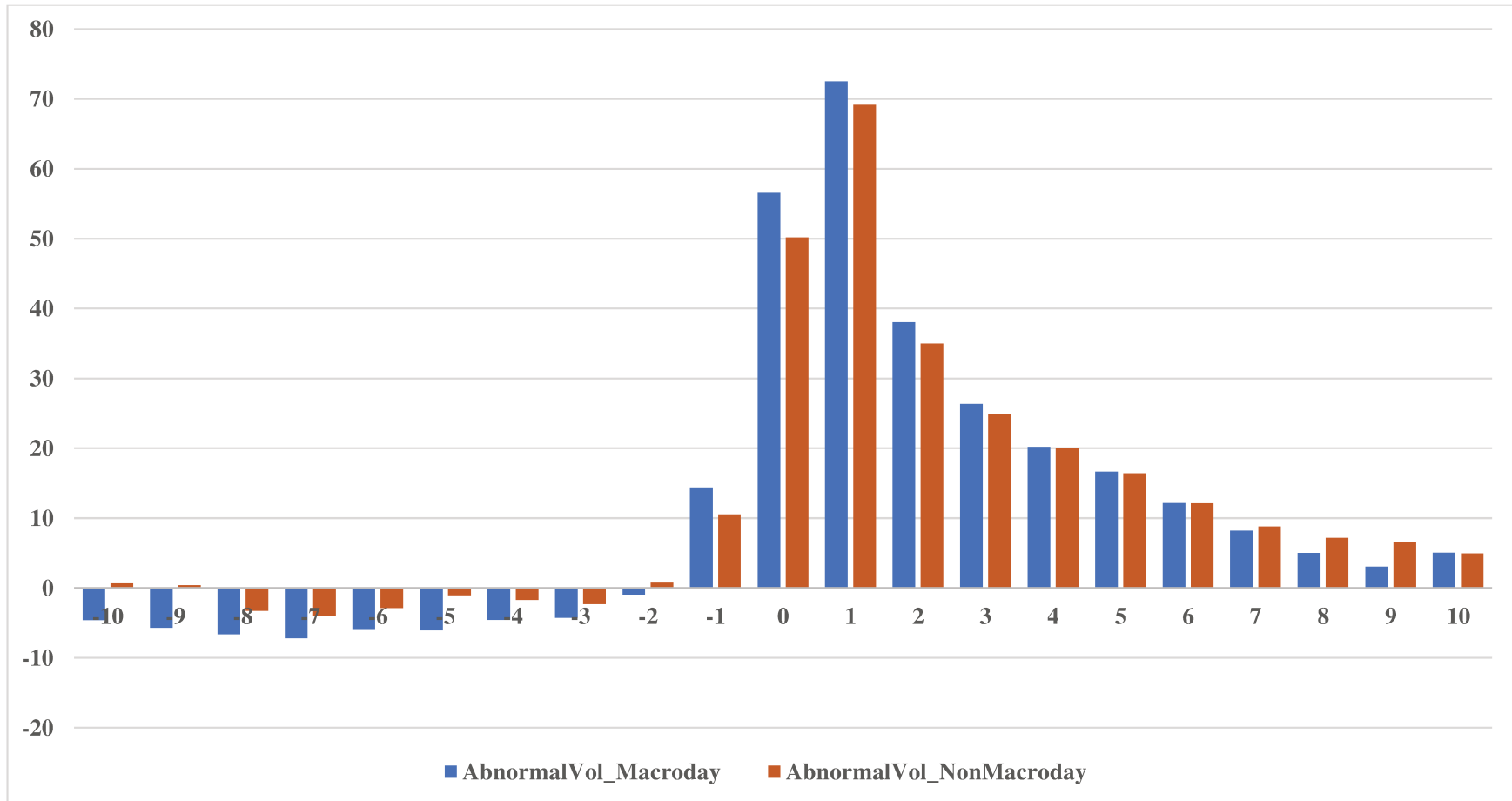


Table 1.1. Motivating Evidence for Model Setup

This table presents the timing relation of daily changes in implied volatility of S&P 100 with the releases of macroeconomic announcements. *Macroday* equals 1 if a macroeconomic announcement is scheduled on time t . Panel A uses raw daily changes while Panel B winsorizes daily changes at $p=0.01$ each tail. *PreMacroday* equals 1 if time t is one day prior to the pre-scheduled announcement date of macroeconomic news, and 0 otherwise. *PostMacroday* equals 1 if time t is one day after the announcement date of macroeconomic news, and 0 otherwise. Year, month, and day-of-week dummies are included accordingly. All columns present OLS regression results with robust standard errors, and t-statistics are reported in the parentheses.

Panel A. Implied Volatility of S&P 100 Index Option

VARIABLES	(1) VXO Change	(2) VXO Change	(3) VXO Change	(4) VXO Change	(5) VXO Change
Macroday	-0.134 (-2.319)		-0.166 (-2.780)	-0.137 (-2.256)	-0.159 (-2.591)
PreMacroday		0.127 (2.187)	0.160 (2.669)	0.146 (2.384)	0.124 (2.038)
PostMacroday					0.137 (2.185)
Constant	0.0335 (1.113)	-0.0357 (-1.191)	-0.000684 (-0.0212)	-0.0723 (-0.478)	-0.107 (-0.703)
N Obs	5,276	5,275	5,275	5,275	5,275
Adj R2	0.001	0.001	0.002	-0.000	0.000

Panel B. Implied Volatility of S&P 100 Index Option, Winsorized

VARIABLES	(1) VXO Change	(2) VXO Change	(3) VXO Change	(4) VXO Change	(5) VXO Change
Macroday	-0.134 (-2.673)		-0.160 (-3.132)	-0.131 (-2.507)	-0.147 (-2.783)
PreMacroday		0.0999 (1.993)	0.132 (2.577)	0.121 (2.303)	0.106 (2.001)
PostMacroday					0.0987 (1.831)
Constant	0.0330 (1.303)	-0.0292 (-1.152)	0.00474 (0.173)	-0.0697 (-0.546)	-0.0949 (-0.738)
N Obs	5,276	5,275	5,275	5,275	5,275
Adj R2	0.001	0.001	0.002	0.001	0.001
Year FE	N	N	N	Y	Y
Month FE	N	N	N	Y	Y
DOW FE	N	N	N	Y	Y

Table 1.2. Summary Statistics

This table presents the summary statistics for variables in the main regression results with the full sample in Panel A, the subsample of expansions in Panel B, and the subsample of recessions in Panel C. *CAR* variables are cumulative abnormal returns over the associated windows using the Fama-French 3-factor pricing model. Following Dellavignall and Pollet (2009), *SUE* is the 11 quantiles of standardized unexpected earnings where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. Following Sheng (2019), *Macroday* is an indicator variable equal to one if there are macroeconomic announcements released on the same day with a firm's quarterly earnings announcement, and zero otherwise. *SameDayEarnings* is the natural log of 1 + the total number of earnings announcements released within the same day by all other firms. *Friday* is an indicator variable equal to one if a firm's earnings announcement takes place on a Friday. *InstitutionalOwnership* is the percentage of a firm's shares held by 13f institutional investors. *AnalystCoverage* is the natural log of 1 + the number of analyst earnings forecasts that are used to form the earnings consensus by I/B/E/S. *StaleConsensus* is the time gap between the date of forming earnings consensus and the date of a firm's earnings announcement. *Size* is the natural log of market capitalization at the previous quarter end. Turnover is trading volume scaled by number of shares outstanding. *Momentum_3* is the holding-period return in the previous quarter, and *Momentum_9* is the 9-month holding-period return before that. *REF* is response to analyst earnings forecast consensus measured by *CAR*(-15, ecd), and *InvestorPI* is investor private information measured by *CAR*(ecd+1,-1), where "ecd" is the date of forming earnings consensus for a firm by I/B/E/S. *InvestorPI Alt* is investor private information alternatively measured by *CAR*(ecd+1,-2).

Panel A. Full Sample						
VarName	Obs	Mean	SD	P25	Median	P75
SUE	99561	6.989	2.937	5	7	9
Macroday	99561	0.265	0.441	0	0	1
SameDayEarnings	99561	6.183	0.845	5.864	6.477	6.766
Friday	99561	0.051	0.221	0	0	0
InstitutionalOwn	88908	0.667	0.231	0.527	0.708	0.841
AnalystCoverage	99561	2.196	0.555	1.792	2.197	2.639
StaleConsensus	99561	-9.324	3.611	-13	-8	-6
Size	99561	14.151	1.63	12.995	14.03	15.165
Turnover	99561	2.015	1.745	0.894	1.494	2.515
Momentum3	99561	0.036	0.253	-0.083	0.035	0.15
Momentum9	99561	0.121	0.44	-0.091	0.111	0.312
CAR(0,1)	99542	-1.317	7.944	-5.266	-1.229	2.777
CAR(2,15)	99291	-10.062	13.754	-20.236	-6.851	-0.117
CAR(-15,-1)	99561	-10.899	14.881	-21.638	-7.197	-0.072
REF	99561	-7.502	11.404	-14.122	-4.783	0.148
InvestorPI	99561	-3.414	6.809	-6.539	-2.055	0.577
CAR(-1,1)	99542	-1.963	8.412	-6.414	-1.765	2.568
CAR(2,30)	96253	-20.917	25.404	-41.797	-13.214	-1.191
CAR(2,45)	86557	-32.123	37.501	-64.921	-19.528	-2.118
CAR(-15,-2)	99561	-10.256	14.116	-20.381	-6.841	-0.067
InvestorPI Alt	99561	-2.77	5.986	-5.193	-1.377	0.345

Panel B. Subsample of Expansions						
VarName	Obs	Mean	SD	P25	Median	P75
SUE	88743	7.025	2.924	5	7	9
Macroday	88743	0.27	0.444	0	0	1
SameDayEarnings	88743	6.194	0.849	5.875	6.491	6.766
Friday	88743	0.051	0.221	0	0	0
InstitutionalOwn	78240	0.663	0.23	0.525	0.703	0.836
AnalystCoverage	88743	2.202	0.559	1.792	2.197	2.639
StaleConsensus	88743	-9.337	3.609	-13	-8	-6
Size	88743	14.182	1.624	13.028	14.059	15.192
Turnover	88743	1.958	1.705	0.876	1.448	2.432
Momentum3	88743	0.048	0.241	-0.067	0.043	0.155
Momentum9	88743	0.145	0.428	-0.064	0.126	0.323
CAR(0,1)	88724	-1.347	7.643	-5.18	-1.231	2.646
CAR(2,15)	88492	-10.212	13.731	-20.838	-6.529	-0.058
CAR(-15,-1)	88743	-10.938	14.827	-22.023	-6.699	0.026
REF	88743	-7.511	11.268	-14.08	-4.506	0.178
InvestorPI	88743	-3.436	6.677	-6.427	-1.976	0.553
CAR(-1,1)	88724	-1.993	8.099	-6.333	-1.751	2.424
CAR(2,30)	85815	-21.314	25.724	-43.788	-12.376	-1.051
CAR(2,45)	77503	-32.919	38.136	-68.399	-18.491	-2.037
CAR(-15,-2)	88743	-10.291	14.043	-20.676	-6.39	0.007
InvestorPI Alt	88743	-2.791	5.871	-5.096	-1.325	0.331
Panel C. Subsample of Recessions						
VarName	Obs	Mean	SD	P25	Median	P75
SUE	10818	6.696	3.022	4	7	9
Macroday	10818	0.225	0.417	0	0	0
SameDayEarnings	10818	6.095	0.814	5.796	6.323	6.721
Friday	10818	0.05	0.219	0	0	0
InstitutionalOwn	10668	0.695	0.236	0.548	0.742	0.883
AnalystCoverage	10818	2.149	0.515	1.792	2.079	2.565
StaleConsensus	10818	-9.211	3.625	-13	-7	-6
Size	10818	13.904	1.654	12.75	13.79	14.914
Turnover	10818	2.486	1.985	1.129	1.95	3.187
Momentum3	10818	-0.069	0.318	-0.23	-0.06	0.091
Momentum9	10818	-0.079	0.479	-0.32	-0.057	0.194
CAR(0,1)	10818	-1.073	10.154	-6.102	-1.209	4.416
CAR(2,15)	10799	-8.759	14.176	-16.972	-9.215	-0.972
CAR(-15,-1)	10818	-10.578	15.444	-19.783	-10.596	-1.688
REF	10818	-7.366	12.723	-14.327	-7.032	-0.313
InvestorPI	10818	-3.225	7.921	-7.324	-2.789	0.932
CAR(-1,1)	10818	-1.706	10.767	-7.261	-1.918	4.162
CAR(2,30)	10438	-17.489	22.8	-31.695	-18.767	-3.629
CAR(2,45)	9054	-25.07	31.387	-44.705	-26.48	-3.468
CAR(-15,-2)	10818	-9.931	14.868	-18.745	-10.167	-1.36
InvestorPI Alt	10818	-2.57	7.046	-5.903	-1.879	0.604

Table 1.3. Macroeconomic Announcements and Immediate Price Responses

This table presents the effects of macroeconomic announcements on immediate price responses to earnings news. The dependent variable is the two-day cumulative Fama-French 3-factor abnormal return. Main explanatory variables and covariates are defined in Table 2. Columns (1) and (2) cover full sample from 1998 to 2017 while columns (3) and (4) use subsamples of observations during expansions and recessions, respectively. Column (1) uses robust standard errors, and columns (2) – (4) cluster standard errors at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly.

Variables	(1)	(2)	(3)	(4)
	CAR(0,1)	CAR(0,1)	CAR(0,1)	CAR(0,1)
	All		Expansion	Recession
SUE	0.824 (73.70)	0.876 (56.59)	0.855 (55.34)	1.186 (18.28)
SUE*Macroday	0.0596 (2.444)	0.0761 (2.916)	0.0624 (2.396)	0.207 (1.388)
Macroday	0.245 (1.342)	-0.405 (-2.066)	-0.314 (-1.608)	-0.886 (-0.792)
SameDayEarnings	0.186 (1.994)	0.267 (2.100)	0.263 (2.058)	-0.191 (-0.317)
Friday	0.447 (1.411)	0.856 (2.323)	1.023 (2.703)	-0.559 (-0.301)
InstitutionalOwnership	-2.238 (-6.727)	-1.414 (-2.892)	-0.973 (-1.997)	-0.0232 (-0.00825)
AnalystCoverage	-0.372 (-1.892)	-1.195 (-4.614)	-1.267 (-4.808)	-1.250 (-1.029)
StaleConsensus	-0.0704 (-3.136)	-0.0675 (-2.562)	-0.0686 (-2.627)	-0.111 (-0.862)
Size	0.416 (6.707)	-0.366 (-3.503)	-0.369 (-3.419)	-0.739 (-1.498)
Turnover	-0.173 (-3.448)	-0.0945 (-1.645)	-0.0789 (-1.288)	-0.146 (-0.638)
Momentum_3	-0.472 (-1.417)	-1.005 (-2.774)	-1.275 (-3.285)	-2.576 (-2.019)
Momentum_9	-0.867 (-4.500)	-0.928 (-4.242)	-1.016 (-4.269)	-3.592 (-3.467)
SUE*SameDayEarnings	-0.0503 (-3.989)	-0.0334 (-2.012)	-0.0374 (-2.257)	0.0493 (0.637)
SUE*Friday	-0.132 (-3.065)	-0.139 (-2.818)	-0.154 (-3.065)	-0.0316 (-0.124)
SUE*InstitutionalOwnership	0.641 (14.30)	0.666 (11.94)	0.574 (10.41)	1.231 (4.358)
SUE*AnalystCoverage	0.0721 (2.756)	0.0958 (2.946)	0.109 (3.304)	0.136 (0.898)
SUE*StaleConsensus	0.00557 (1.858)	0.00871 (2.566)	0.00898 (2.645)	0.0128 (0.766)
SUE*Size	-0.0580 (-7.031)	-0.0695 (-6.553)	-0.0635 (-6.002)	-0.157 (-3.545)

SUE*Turnover	0.00116 (0.180)	-0.000288 (-0.0406)	-0.00623 (-0.823)	0.0228 (0.794)
SUE*Momentum_3	-0.0291 (-0.682)	0.00325 (0.0723)	0.0411 (0.852)	-0.0316 (-0.197)
SUE*Momentum_9	0.0506 (2.058)	0.0816 (3.019)	0.0957 (3.284)	0.193 (1.479)
Constant	-7.372 (-87.16)	-8.803 (-9.873)	-8.833 (-10.31)	-9.607 (-15.11)
N Obs	88,900	88,900	78,232	10,668
Adj R2	0.105	0.173	0.183	0.169
Standard Errors	Robust	Clustered	Clustered	Clustered
FE YYYYQ	N	Y	Y	Y
FE Firm	N	Y	Y	Y

Table 1.4. Macroeconomic Announcements and Delayed Price Responses

This table presents the effects of macroeconomic announcements on delayed price responses to earnings surprises. The dependent variable is the cumulative Fama-French 3-factor abnormal return in the window [2,15] days after a firm's quarterly earnings announcement. Main explanatory variables and covariates are defined in Table 2. Columns (1) and (2) cover full sample from 1998 to 2017 while columns (3) and (4) use subsamples of observations during expansions and recessions, respectively. Column (1) uses robust standard errors, and columns (2) – (4) cluster standard errors at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)
	CAR(2,15)	CAR(2,15)	CAR(2,15)	CAR(2,15)
	All		Expansion	Recession
SUE	0.163 (7.998)	0.130 (9.008)	0.126 (8.688)	0.186 (2.330)
SUE*Macroday	-0.191 (-4.552)	-0.0961 (-3.136)	-0.0996 (-3.285)	-0.0485 (-0.238)
Macroday	5.148 (16.25)	0.615 (2.608)	0.580 (2.469)	1.185 (0.793)
SameDayEarnings	-0.308 (-1.840)	-0.179 (-1.318)	-0.0840 (-0.611)	-1.051 (-1.424)
Friday	-1.183 (-2.061)	0.298 (0.692)	0.219 (0.494)	2.478 (1.125)
InstitutionalOwnership	3.299 (5.532)	2.003 (3.372)	2.165 (3.617)	0.390 (0.109)
AnalystCoverage	2.564 (7.528)	0.00534 (0.0191)	0.0126 (0.0457)	0.526 (0.330)
StaleConsensus	-0.0808 (-2.029)	0.0176 (0.583)	0.00447 (0.148)	0.301 (1.678)
Size	-0.0902 (-0.795)	-0.972 (-8.145)	-0.924 (-7.752)	-2.953 (-4.281)
Turnover	0.206 (2.466)	0.146 (1.886)	0.0348 (0.437)	0.583 (1.754)
Momentum_3	-0.949 (-1.749)	-2.158 (-4.583)	-2.030 (-4.000)	-5.715 (-3.370)
Momentum_9	-0.948 (-2.962)	-0.816 (-2.943)	-0.723 (-2.513)	-2.313 (-1.579)
Constant	-12.85 (-83.01)	-27.45 (-21.37)	-27.31 (-21.33)	-20.54 (-23.15)
SUE*Covar	Y	Y	Y	Y
N Obs	88,841	88,841	78,176	10,665
Adj R2	0.042	0.630	0.680	0.302
Standard Errors	Robust	Clustered	Clustered	Clustered
FE YYYYQ	N	Y	Y	Y
FE Firm	N	Y	Y	Y

Table 1.5. Scaled Immediate and Delayed Price Responses to Earnings Surprises

This table presents and compares the effects of macroeconomic announcements on immediate and delayed price responses to earnings news during expansions and recessions. The dependent variable for columns (1) and (2) is the scaled two-day cumulative Fama-French 3-factor abnormal return. Scaling in this table means being first net of mean and then divided by standard deviation, where both mean and standard deviation are subsample-specific. The dependent variable for columns (3) and (4) is the scaled cumulative Fama-French 3-factor abnormal return in the window [2,15] days after a firm's quarterly earnings announcement. Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)
	Scaled CAR(0,1)		Scaled CAR(2,15)	
	Expansion	Recession	Expansion	Recession
SUE	0.112 (55.34)	0.117 (18.28)	0.00917 (8.688)	0.0131 (2.330)
SUE*Macroday	0.00816 (2.396)	0.0204 (1.388)	-0.00726 (-3.285)	-0.00342 (-0.238)
Macroday	-0.0411 (-1.608)	-0.0873 (-0.792)	0.0422 (2.469)	0.0836 (0.793)
N Obs	78,232	10,668	78,176	10,665
Adj R2	0.183	0.169	0.680	0.302
Constant	Y	Y	Y	Y
Covariates	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y

Table 1.6. Decomposition of CAR(-15,-1) into Response to Earnings Forecast (REF) and Investor Private Information (InvestorPI)

This table presents the effects of macroeconomic announcements on pre-earnings-announcement drifts. CAR(-15,-1) is the cumulative Fama-French 3-factor abnormal return in the window [-15,-1] days before a firm's quarterly earnings announcement. CAR(-15,-1) is decomposed into the sum of two terms: *REF* and *InvestorPI*. *REF* is response to analyst earnings forecast consensus measured by CAR(-15, ecd), and *InvestorPI* is investor private information measured by CAR(ecd+1,-1), where "ecd" is the date of forming earnings consensus for a firm by I/B/E/S. Main explanatory variables and covariates are defined in Table 2. Columns (1), (4) and (7) cover full sample from 1997 to 2016; columns (2), (5) and (8) and columns (3), (6) and (9) use subsamples of observations during expansions and recessions, respectively. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CAR(-15,-1)			REF			InvestorPI		
	All	Expansion	Recession	All	Expansion	Recession	All	Expansion	Recession
SUE	0.296 (18.62)	0.292 (18.33)	0.249 (2.845)	0.189 (14.21)	0.180 (13.44)	0.246 (3.430)	0.108 (11.48)	0.111 (11.54)	0.0267 (0.549)
SUE*Macroday	-0.0912 (-2.878)	-0.107 (-3.448)	0.0830 (0.393)	-0.0489 (-1.945)	-0.0470 (-1.880)	-0.0534 (-0.346)	-0.0475 (-2.315)	-0.0659 (-3.208)	0.123 (0.948)
Macroday	0.512 (2.131)	0.699 (2.988)	-1.637 (-1.033)	-0.00870 (-0.0453)	-0.0227 (-0.119)	-0.223 (-0.192)	0.584 (3.734)	0.786 (4.994)	-1.282 (-1.348)
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	88,908	78,240	10,668	88,908	78,240	10,668	88,908	78,240	10,668
Adj R2	0.633	0.684	0.308	0.547	0.598	0.262	0.403	0.451	0.179
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.7. Main Results: Mitigating Concerns of Selective Disclosure prior to Regulation Fair Disclosure (Reg FD)

This table replicates the main results using the observations in the post-Reg FD regime exclusively. Observations included in this table are from 2001 to 2017. CARs are the cumulative Fama-French 3-factor abnormal returns. CAR(-15,-1) is decomposed into the sum of two terms: *REF* and *InvestorPI*. *REF* is response to analyst earnings forecast consensus measured by CAR(-15, ecd), and *InvestorPI* is investor private information measured by CAR(ecd+1,-1), where “ecd” is the date of forming earnings consensus for a firm by I/B/E/S. Main explanatory variables and covariates are defined in Table 2. Subsamples of observations during expansions and recessions are employed, accordingly. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR(0,1)		CAR(2,15)		CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.889 (53.97)	1.186 (18.28)	0.127 (8.630)	0.186 (2.330)	0.257 (16.09)	0.249 (2.845)	0.153 (11.47)	0.246 (3.430)	0.103 (10.67)	0.0267 (0.549)
SUE*Macroday	0.0570 (2.114)	0.207 (1.388)	-0.0867 (-2.914)	-0.0485 (-0.238)	-0.0761 (-2.537)	0.0830 (0.393)	-0.0169 (-0.697)	-0.0534 (-0.346)	-0.0634 (-3.178)	0.123 (0.948)
Macroday	-0.312 (-1.551)	-0.886 (-0.792)	0.543 (2.375)	1.185 (0.793)	0.457 (2.016)	-1.637 (-1.033)	0.0198 (0.107)	-0.223 (-0.192)	0.487 (3.199)	-1.282 (-1.348)
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	65,123	10,668	65,086	10,665	65,124	10,668	65,124	10,668	65,124	10,668
Adj R2	0.187	0.169	0.663	0.302	0.673	0.308	0.567	0.262	0.449	0.179
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.8. Main Results: Mitigating Concerns of Illegal Insider Trades

This table replicates the main results excluding observations of firms ever involved with illegal insider trades. Observations included in this table are from 1998 to 2017. CARs are the cumulative Fama-French 3-factor abnormal returns. CAR(-15,-1) is decomposed into the sum of two terms: *REF* and *InvestorPI*. *REF* is response to analyst earnings forecast consensus measured by CAR(-15, ecd), and *InvestorPI* is investor private information measured by CAR(ecd+1,-1), where “ecd” is the date of forming earnings consensus for a firm by I/B/E/S. Main explanatory variables and covariates are defined in Table 2. Subsamples of observations during expansions and recessions are employed, accordingly. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR(0,1)		CAR(2,15)		CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.852 (53.48)	1.187 (17.28)	0.133 (8.821)	0.212 (2.522)	0.303 (18.38)	0.277 (3.050)	0.188 (13.62)	0.262 (3.502)	0.114 (11.50)	0.0368 (0.725)
SUE*Macroday	0.0606 (2.249)	0.171 (1.090)	-0.108 (-3.444)	-0.0537 (-0.248)	-0.116 (-3.662)	-0.00923 (-0.0422)	-0.0556 (-2.152)	-0.105 (-0.650)	-0.0704 (-3.327)	0.0792 (0.583)
Macroday	-0.292 (-1.442)	-0.625 (-0.536)	0.648 (2.675)	1.319 (0.829)	0.762 (3.172)	-0.743 (-0.452)	-0.00642 (-0.0327)	0.285 (0.235)	0.849 (5.227)	-0.868 (-0.876)
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	72,132	9,785	72,083	9,783	72,140	9,785	72,140	9,785	72,140	9,785
Adj R2	0.187	0.174	0.684	0.298	0.690	0.313	0.605	0.272	0.453	0.175
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.9. Main Results: Mitigating Concerns of Analyst Earnings Forecasts Issued Post I/B/E/S Earnings Consensus

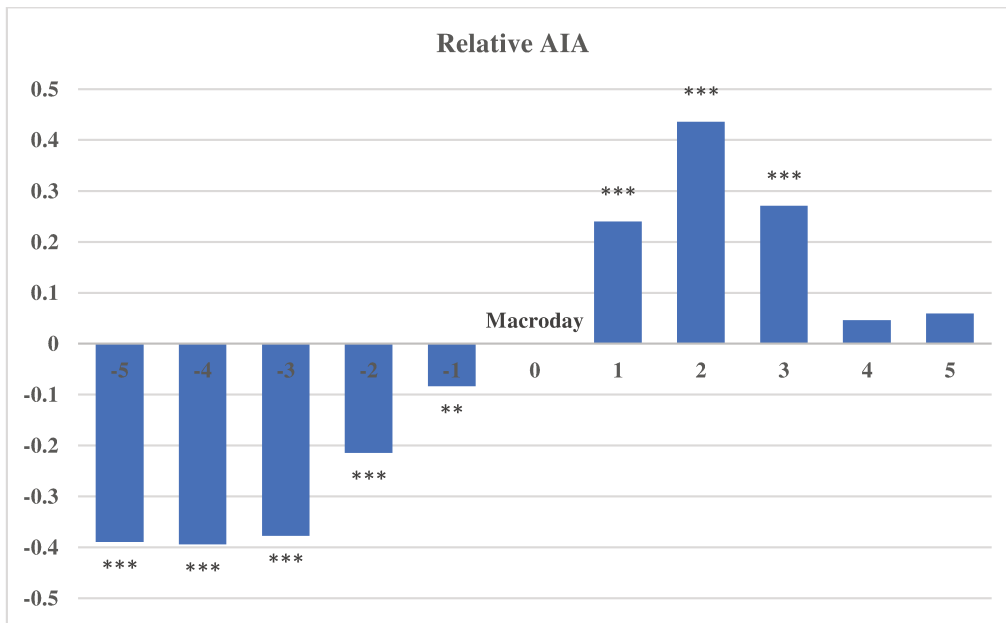
This table replicates the main results exclusively using the observations without analyst earnings forecasts issued after I/B/E/S forms a firm's earnings consensus but still before the date of this firm's actual earnings announcement. Observations included in this table are from 1998 to 2017. CARs are the cumulative Fama-French 3-factor abnormal returns. CAR(-15,-1) is decomposed into the sum of two terms: *REF* and *InvestorPI*. *REF* is response to analyst earnings forecast consensus measured by CAR(-15, ecd), and *InvestorPI* is investor private information measured by CAR(ecd+1,-1), where "ecd" is the date of forming earnings consensus for a firm by I/B/E/S. Main explanatory variables and covariates are defined in Table 2. Subsamples of observations during expansions and recessions are employed, accordingly. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR(0,1)		CAR(2,15)		CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.855 (55.21)	1.194 (18.35)	0.125 (8.610)	0.182 (2.271)	0.290 (18.20)	0.240 (2.723)	0.179 (13.34)	0.244 (3.386)	0.110 (11.49)	0.0208 (0.426)
SUE*Macroday	0.0632 (2.422)	0.189 (1.263)	-0.0980 (-3.226)	-0.0411 (-0.201)	-0.105 (-3.377)	0.106 (0.500)	-0.0457 (-1.822)	-0.0489 (-0.315)	-0.0656 (-3.188)	0.140 (1.073)
Macroday	-0.319 (-1.629)	-0.752 (-0.669)	0.569 (2.416)	1.108 (0.737)	0.689 (2.931)	-1.788 (-1.121)	-0.0324 (-0.169)	-0.261 (-0.224)	0.787 (4.996)	-1.381 (-1.445)
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	78,048	10,642	77,992	10,639	78,056	10,642	78,056	10,642	78,056	10,642
Adj R2	0.182	0.170	0.679	0.303	0.683	0.308	0.598	0.262	0.451	0.179
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Figure A1.1. Daily Bloomberg Readership Around Macroeconomic Announcements

This figure presents OLS regression coefficients of daily measures of investor attention, derived from Bloomberg readership data following Ben-Rephael, Da and Israelsen (2017), onto daily timing indicators in the window $[-5,+5]$ around macroeconomic announcements ($t=0$) in Panel A and in the window $[-10,+10]$ in Panel B. The vertical axis are regression coefficients of daily timing indicators $-5, \dots, -1$ and $1, \dots, 5$, scaling the AIA on days of macroeconomic announcements into zero. The horizontal axis is relative timeline. Year-, month-, and day-of-week- fixed effects are included in the regression. *** and ** represent statistical significance at the 1% and 5% level, respectively.

Panel A. Relative Abnormal Investor Attention $[-5,+5]$ around Macroday



Panel B. Relative Abnormal Investor Attention $[-10,+10]$ around Macroday

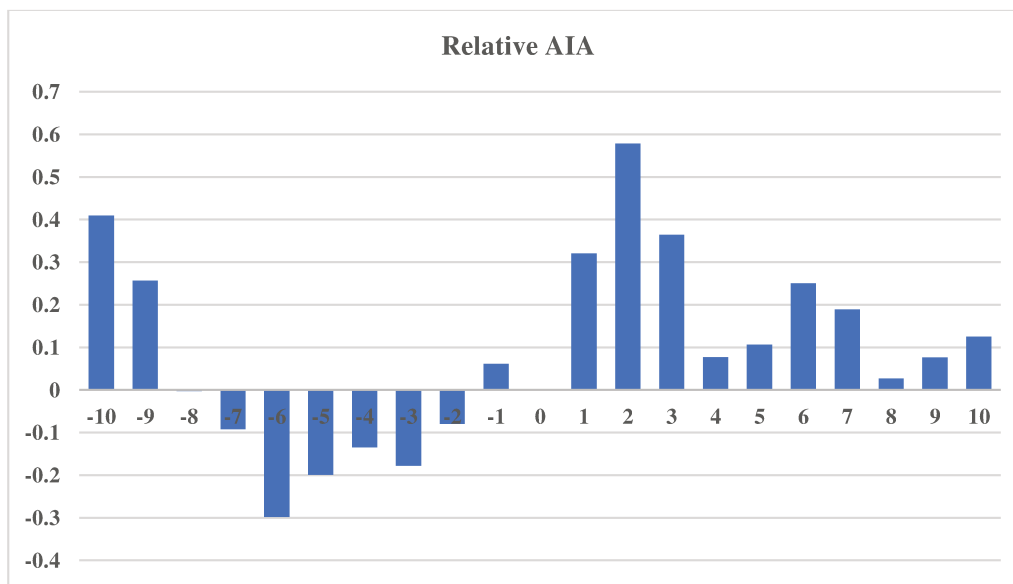
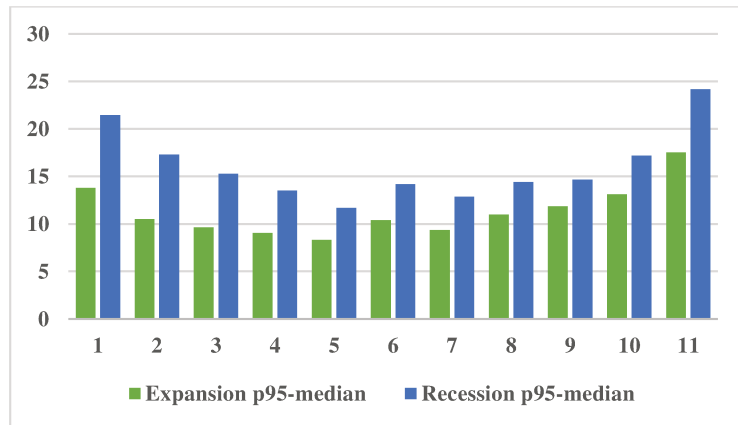


Figure A1.2. Immediate Price Responses: Expansions and Recessions

This figure compares the dispersions of immediate price responses by earnings surprise sorts (*SUE*) for expansions and recessions, respectively. Panel A presents the differential in Fama-French 3-factor CAR(0,1) between the 75th and 50th (or 25th) percentiles while Panel B between the 95th and 50th (or 25th) percentiles. Following Dellavignall and Pollet (2009), *SUE* is the 11 quantiles of standardized unexpected earnings where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. The vertical axis is in the unit of percentage points.

Panel A. CAR(0,1) differential between 75th and 50th (or 25th)



Panel B. CAR(0,1) differential between 95th and 50th (or 25th)

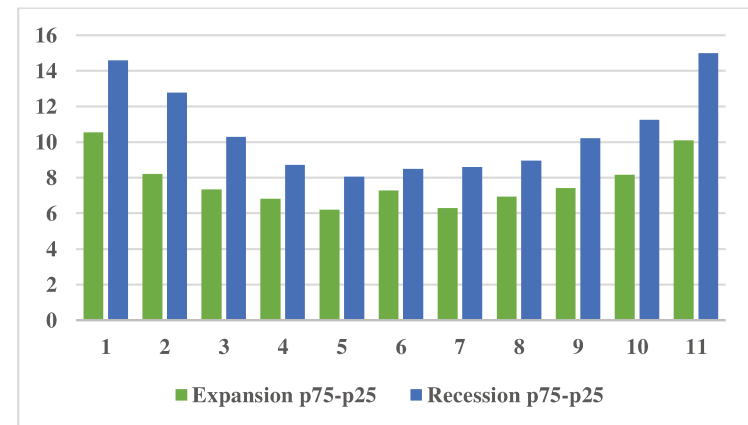
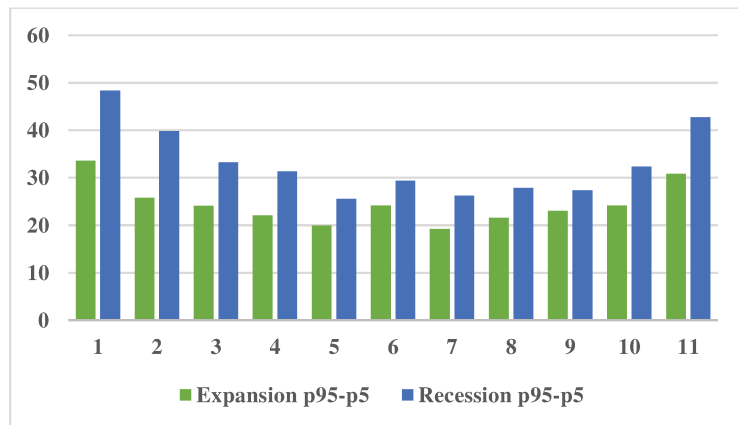
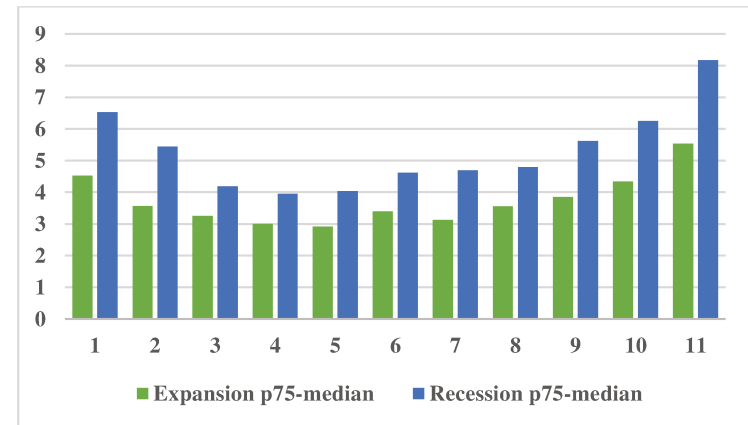


Figure A1.3. Abnormal Trading Volume around Earnings Announcements

This figure compares the abnormal trading volume around firm-earnings news announced on *Macroday* with that on *Non-Macroday*. The vertical axis is abnormal trading volume defined as in Hershleifer, Lim and Teoh (2009). The horizontal axis is relative timing around firm earnings announcement. Absolute earnings surprises are sorted into quintiles. This figure shows the comparison with absolute earnings surprise quintile=1, 2, 4, and 5, respectively.

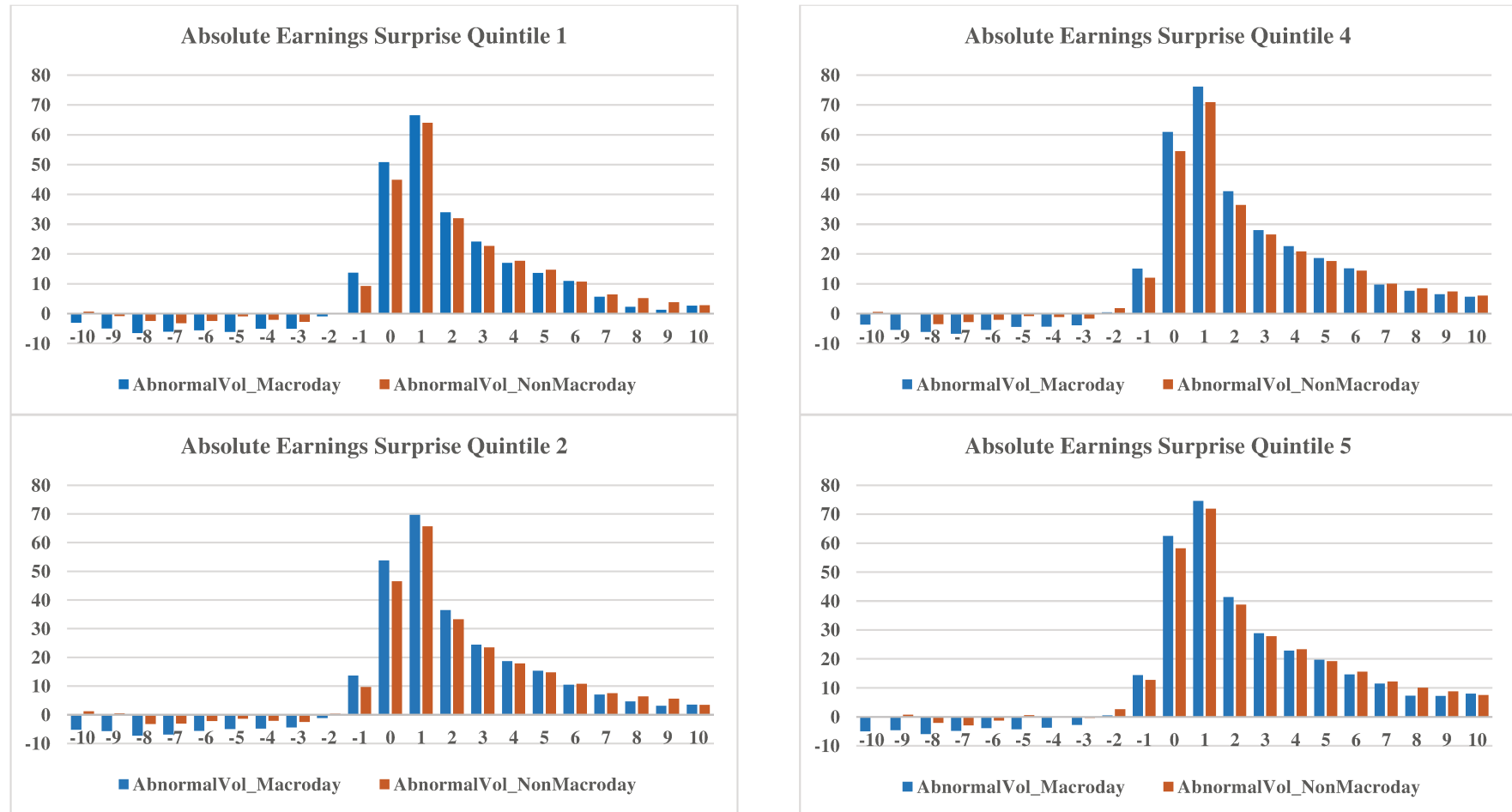


Table A1.1. Detailed Definitions for Variables

This table presents the detailed definitions for variables in Table 2.

Variables/Definitions	
SUE	Following Dellavignal and Pollet (2009), SUE is the 11 quantiles of standardized unexpected earnings where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises.
Macroday	Following Sheng (2019), Macroday is an indicator variable equal to one if there are macroeconomic announcements released on the same day with a firm's quarterly earnings announcement, and zero otherwise. Included macroeconomic announcements are FOMC, Nonfarm Payroll, ISM PMI and Personal Consumption.
SameDayEarnings Friday	The natural log of 1 + the total number of earnings announcements released within the same day by all other firms. An indicator variable equal to one if a firm's earnings announcement takes place on a Friday.
InstitutionalOwnership AnalystCoverage	The percentage of a firm's shares held by 13f institutional investors. The natural log of 1 + the number of analyst earnings forecasts that are used to form the earnings consensus by I/B/E/S. Observations of earnings consensus with at least three analyst earnings forecasts are included for regressions.
StaleConsensus	The time gap between the date of I/B/E/S forming earnings consensus and the date of a firm's earnings announcement, in units of days. Observations of earnings consensus formed within the [-15,-2] window are included for regressions.
Size	The natural log of market capitalization at the previous quarter end. Market capitalization is the product of end-of-quarter price per share and the number of shares outstanding.
Turnover	Trading volume scaled by number of shares outstanding, winsorized at $p = 0.005$ for each tail.
Momentum_3	Holding-period return of the quarter before a firm's quarterly earnings announcement.
Momentum_9	Holding-period return of the 9-month period [-12,-4] months relative to a firm's quarterly earnings announcement.
CAR(0,1)	Immediate Price Response: Cumulative abnormal return over the [0,1] window; $t = 0$ is a firm's quarterly earnings announcement date.
CAR(2,15)	Delayed Price Response: Cumulative abnormal return over the [2,15] window.
CAR(-15,-1)	Pre-Earning Announcement Drift: Cumulative abnormal return over the [-15,-1] window.
REF	Response to Public Information: Cumulative abnormal return over the [-15,ConsensusDate] window.
InvestorPI	Investor Private Information: Cumulative abnormal return over the [ConsensusDate+1,-1] window.
CAR(-1,1)	Immediate Price Response: Cumulative abnormal return over the [-1,1] window.
CAR(2,30)	Delayed Price Response: Cumulative abnormal return over the [2,30] window.
CAR(2,45)	Delayed Price Response: Cumulative abnormal return over the [2,45] window.
CAR(-15,-2)	Pre-Earning Announcement Drift: Cumulative abnormal return over the [-15,-2] window.
InvestorPI Alt	Investor Private Information: Cumulative abnormal return over the [ConsensusDate+1,-2] window.

Table A1.2. Macroeconomic Announcements and Immediate Price Responses to Earnings Surprises

This table presents the effects of macroeconomic announcements on immediate price responses to earnings news in terms of cumulative abnormal returns generated via alternative empirical models. Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cart 4-Factor CAR(0,1)		CAPM CAR(0,1)		Market Model CAR(0,1)		Excess Market CAR(0,1)	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.856	1.187	0.858	1.199	0.860	1.202	0.835	1.199
	(54.88)	(17.62)	(55.76)	(18.30)	(55.94)	(18.32)	(57.38)	(18.13)
SUE*Macroday	0.0634	0.186	0.0620	0.173	0.0593	0.168	0.0658	0.195
	(2.412)	(1.208)	(2.376)	(1.143)	(2.267)	(1.112)	(2.581)	(1.289)
Macroday	-0.118	-3.300	-0.261	-0.335	-0.250	-0.290	-0.314	-0.571
	(-0.596)	(-2.856)	(-1.332)	(-0.295)	(-1.277)	(-0.255)	(-1.648)	(-0.501)
Constant	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	78,227	10,668	78,227	10,668	78,227	10,668	85,253	10,822
Adj R2	0.183	0.162	0.182	0.171	0.142	0.162	0.137	0.156
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y

Table A1.3. Macroeconomic Announcements and Delayed Price Responses to Earnings Surprises

This table presents the effects of macroeconomic announcements on post-earnings-announcement drifts in terms of cumulative abnormal returns generated via alternative empirical models. Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Carhart 4-Factor CAR(2,15)		CAPM CAR(2,15)		Market Model CAR(2,15)		Excess Market CAR(2,15)	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.129 (8.553)	0.195 (2.236)	0.119 (8.235)	0.232 (2.981)	0.116 (8.090)	0.225 (2.931)	0.109 (7.828)	0.272 (3.516)
SUE*Macroday	-0.0973 (-3.136)	-0.133 (-0.606)	-0.0894 (-2.963)	-0.0549 (-0.279)	-0.0769 (-2.564)	-0.0428 (-0.218)	-0.0813 (-2.694)	-0.0458 (-0.231)
Macroday	0.386 (1.599)	1.147 (0.717)	0.646 (2.766)	0.954 (0.661)	0.551 (2.378)	0.672 (0.467)	0.568 (2.451)	0.545 (0.376)
Constant	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	78,166	10,670	78,144	10,665	78,144	10,665	85,188	10,818
Adj R2	0.664	0.361	0.680	0.290	0.082	0.132	0.082	0.137
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y

Table A1.4. Extended Windows for Macroday

This table presents the trailing effects of macroeconomic announcements as inspired by the Bloomberg readership data in Figure A1. *Macroday* is an indicator variable for days with macroeconomic announcements. Alternative extended windows are (0,1), (0,2), and (0,3) as in columns (1) and (2), columns (3) and (4), and columns (5) and (6), respectively. *Macroday_alt* (0,1) is an indicator variable for days with macroeconomic announcements or days right after macroeconomic announcements being released in the previous day. *Macroday_alt* (0,2) and *Macroday_alt* (0,3) are similarly defined. The dependent variable is the two-day cumulative Fama-French 3-factor abnormal return CAR(0,1). Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Macroday_alt (0,1)		Macroday_alt (0,2)		Macroday_alt (0,3)	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.839 (51.09)	1.213 (17.30)	0.838 (49.58)	1.223 (17.21)	0.841 (48.70)	1.217 (17.08)
SUE*Macroday_alt	0.0895 (3.594)	0.0570 (0.378)	0.0859 (3.449)	0.0185 (0.129)	0.0748 (2.957)	0.0386 (0.281)
Macroday_alt	-0.581 (-3.059)	0.120 (0.105)	-0.587 (-3.073)	0.325 (0.301)	-0.541 (-2.790)	0.355 (0.346)
Constant	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y
N Obs	78,225	10,668	78,227	10,668	78,227	10,668
Adj R2	0.183	0.169	0.183	0.169	0.183	0.169
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y

Table A1.5. Scaled Immediate and Delayed Price Responses to Earnings Surprises

This table presents the effects of macroeconomic announcements on immediate price responses to earnings news and post-earnings-announcement drifts. The dependent variable for columns (1) and (2) is the scaled two-day cumulative abnormal return using alternative models. Scaling in this table means being first net of mean and then divided by standard deviation. The dependent variable for columns (3) and (4) is scaled the cumulative abnormal return, using alternative models, in the window [2,15] days after a firm's quarterly earnings announcement. Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

	(1)	(2)	(3)	(4)
Panel A: Carhart 4-Factor				
Variables	Scaled CAR(0,1)		Scaled CAR(2,15)	
	Expansion	Recession	Expansion	Recession
SUE	0.111 (54.88)	0.112 (17.62)	0.00905 (8.553)	0.0122 (2.236)
SUE*Macroday	0.00820 (2.412)	0.0176 (1.208)	-0.00681 (-3.136)	-0.00828 (-0.606)
Macroday	-0.0152 (-0.596)	-0.312 (-2.856)	0.0270 (1.599)	0.0715 (0.717)
N Obs	78,227	10,668	78,144	10,665
Adj R2	0.183	0.162	0.664	0.361
Panel B: CAPM				
Variables	Scaled CAR(0,1)		Scaled CAR(2,15)	
	Expansion	Recession	Expansion	Recession
SUE	0.112 (55.76)	0.117 (18.30)	0.00843 (8.235)	0.0168 (2.981)
SUE*Macroday	0.00810 (2.376)	0.0169 (1.143)	-0.00634 (-2.963)	-0.00399 (-0.279)
Macroday	-0.0340 (-1.332)	-0.0328 (-0.295)	0.0458 (2.766)	0.0693 (0.661)
N Obs	78,227	10,668	78,144	10,665
Adj R2	0.182	0.171	0.680	0.290

Panel C: Market Model

Variables	Scaled CAR(0,1)		Scaled CAR(2,15)	
	Expansion	Recession	Expansion	Recession
SUE	0.115 (55.94)	0.118 (18.32)	0.0141 (8.090)	0.0182 (2.931)
SUE*Macroday	0.00793 (2.267)	0.0165 (1.112)	-0.00935 (-2.564)	-0.00346 (-0.218)
Macroday	-0.0335 (-1.277)	-0.0284 (-0.255)	0.0669 (2.378)	0.0543 (0.467)
N Obs	78,227	10,668	78,144	10,665
Adj R2	0.142	0.162	0.082	0.132

Panel D: Raw Return in Excess of Market

Variables	Scaled CAR(0,1)		Scaled CAR(2,15)	
	Expansion	Recession	Expansion	Recession
SUE	0.112 (57.38)	0.117 (18.13)	0.0129 (7.828)	0.0216 (3.516)
SUE*Macroday	0.00886 (2.581)	0.0190 (1.289)	-0.00960 (-2.694)	-0.00364 (-0.231)
Macroday	-0.0423 (-1.648)	-0.0556 (-0.501)	0.0671 (2.451)	0.0433 (0.376)
N Obs	85,253	10,822	85,188	10,818
Adj R2	0.137	0.156	0.082	0.137
Constant	Y	Y	Y	Y
Covariates	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y

Table A1.6. Decomposition of CAR(-15,-1) into REF and InvestorPI

This table presents the effects of macroeconomic announcements on pre-earnings-announcement drifts. CAR(-15,-1) is the cumulative abnormal return, using alternative models, in the window [-15,-1] days before a firm's quarterly earnings announcement. CAR(-15,-1) is decomposed into the sum of two terms: *REF* and *InvestorPI*. *REF* is the cumulative abnormal return from $t = -15$ to earnings consensus date, and *InvestorPI* is the cumulative abnormal return from the next day of earnings consensus date to $t = -1$. Main explanatory variables and covariates are defined in Table 2. Columns (1), (3) and (5) use the subsample expansions, and columns (2), (4) and (6) use the subsample of recessions. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Carhart 4-Factor						
Variables	CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.290 (16.54)	0.251 (2.502)	0.177 (12.13)	0.225 (2.776)	0.112 (11.23)	0.0424 (0.780)
SUE*Macroday	-0.110 (-3.315)	-0.0590 (-0.257)	-0.0460 (-1.744)	-0.0895 (-0.529)	-0.0655 (-3.087)	0.0470 (0.331)
Macroday	1.040 (4.123)	-3.183 (-1.842)	0.287 (1.411)	-1.268 (-0.994)	0.759 (4.638)	-1.965 (-1.869)
N Obs	78,235	10,668	78,235	10,668	78,235	10,668
Adj R2	0.668	0.468	0.587	0.513	0.468	0.227
Panel B: CAPM						
Variables	CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.300 (18.40)	0.317 (3.624)	0.186 (13.51)	0.292 (4.052)	0.115 (11.74)	0.0480 (0.961)
SUE*Macroday	-0.114 (-3.571)	0.114 (0.527)	-0.0519 (-2.039)	-0.0363 (-0.227)	-0.0683 (-3.300)	0.120 (0.925)
Macroday	0.729 (3.046)	-1.781 (-1.096)	-0.0382 (-0.198)	-0.281 (-0.233)	0.833 (5.226)	-1.242 (-1.307)
N Obs	78,235	10,668	78,235	10,668	78,235	10,668
Adj R2	0.677	0.321	0.597	0.291	0.448	0.189

Panel C: Market Model

Variables	CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.300 (18.74)	0.320 (3.678)	0.184 (14.30)	0.304 (4.279)	0.113 (12.82)	0.0504 (1.017)
SUE*Macroday	-0.113 (-3.597)	0.149 (0.689)	-0.0620 (-2.608)	-0.0495 (-0.314)	-0.0559 (-2.934)	0.142 (1.101)
Macroday	0.748 (3.189)	-1.402 (-0.861)	0.373 (2.086)	0.0914 (0.0769)	0.447 (3.093)	-1.190 (-1.253)
N Obs	78,235	10,668	78,235	10,668	78,235	10,668
Adj R2	0.083	0.148	0.076	0.116	0.087	0.131

Panel D: Raw Return in Excess of Market

Variables	CAR(-15,-1)		REF		InvestorPI	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.311 (19.98)	0.349 (3.889)	0.192 (15.33)	0.337 (4.596)	0.117 (13.67)	0.0481 (0.967)
SUE*Macroday	-0.114 (-3.634)	0.162 (0.734)	-0.0617 (-2.590)	-0.0461 (-0.276)	-0.0573 (-3.003)	0.147 (1.147)
Macroday	0.706 (3.011)	-1.379 (-0.827)	0.396 (2.202)	0.0771 (0.0611)	0.384 (2.668)	-1.113 (-1.184)
N Obs	85,264	10,822	85,264	10,822	85,264	10,822
Adj R2	0.083	0.150	0.077	0.116	0.081	0.126
Constant	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y

Table A1.7. Alternative Windows for Main Results

This table presents the effects of macroeconomic announcements but using alternative windows to the main results. All *CAR* variables are cumulative Fama-French 3-factor abnormal returns with associated windows. Main explanatory variables and covariates are defined in Table 2. *InvestorPI Alt* is the cumulative abnormal return from the next day of earnings consensus date to $t = -2$. Columns (1), (3), (5) and (7), and columns (2), (4), (6) and (8) use subsamples of observations during expansions and recessions, respectively. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Variables	CAR(-1,1)		CAR(2,45)		CAR(-15,-2)		InvestorPI Alt	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.885 (55.92)	1.223 (18.13)	0.166 (5.944)	-0.121 (-0.756)	0.260 (16.65)	0.223 (2.667)	0.0790 (8.785)	-0.0102 (-0.240)
SUE*Macroday	0.0531 (1.964)	0.184 (1.188)	-0.149 (-2.568)	0.646 (1.597)	-0.0961 (-3.217)	0.109 (0.543)	-0.0568 (-2.953)	0.171 (1.479)
Macroday	-0.201 (-0.989)	-0.750 (-0.648)	0.957 (2.106)	-3.157 (-1.052)	0.588 (2.606)	-1.765 (-1.166)	0.681 (4.587)	-1.587 (-1.856)
Constant	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y
N Obs	78,232	10,668	69,510	8,968	78,240	10,668	78,240	10,668
Adj R2	0.223	0.184	0.867	0.575	0.668	0.290	0.421	0.177
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y

Table A1.8. Robustness Checks for Investor Private Information

This table presents the effects of macroeconomic announcements on *InvestorPI* using alternative models. *InvestorPI* is the cumulative abnormal return from the next day of a firm's earnings consensus date to $t=-1$. Main explanatory variables and covariates are defined in Table 2. Regressions in columns (1) and (2) use the observations in the post-Reg FD regime exclusively (from 2011 to 2016). Columns (3) and (4) remove firms ever involved with illegal insider trades (IIT) that are prosecuted by SEC. Columns (5) and (6) remove firm-quarter observations with "post-consensus forecasts (PCF)", that is, when there are analyst earnings forecasts issued after a firm's earnings consensus has been formed by I/B/E/S. Columns (1), (3) and (5) use the subsample expansions, and columns (2), (4) and (6) use the subsample of recessions. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Carhart 4-Factor						
Regime	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.103 (10.48)	0.0424 (0.780)	0.115 (11.20)	0.0590 (1.046)	0.111 (11.18)	0.0352 (0.645)
SUE*Macroday	-0.0587 (-2.883)	0.0470 (0.331)	-0.0700 (-3.208)	0.00219 (0.0149)	-0.0651 (-3.064)	0.0634 (0.445)
Macroday	0.480 (3.076)	-1.965 (-1.869)	0.827 (4.904)	-1.528 (-1.408)	0.758 (4.629)	-2.076 (-1.963)
N Obs	65,119	10,668	72,136	9,785	78,051	10,642
Adj R2	0.439	0.227	0.472	0.225	0.467	0.227
Panel B: CAPM						
Regime	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.104 (10.58)	0.0480 (0.961)	0.120 (11.85)	0.0529 (1.010)	0.114 (11.70)	0.0439 (0.880)
SUE*Macroday	-0.0630 (-3.136)	0.120 (0.925)	-0.0759 (-3.566)	0.0655 (0.483)	-0.0675 (-3.256)	0.134 (1.033)
Macroday	0.550 (3.587)	-1.242 (-1.307)	0.911 (5.549)	-0.739 (-0.743)	0.829 (5.189)	-1.308 (-1.372)
N Obs	65,119	10,668	72,136	9,785	78,051	10,642
Adj R2	0.445	0.189	0.450	0.188	0.448	0.189

Panel C: Market Model

Regime	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.102 (11.47)	0.0480 (0.961)	0.119 (13.08)	0.0529 (1.010)	0.113 (12.80)	0.0439 (0.880)
SUE*Macroday	-0.0495 (-2.655)	0.120 (0.925)	-0.0626 (-3.207)	0.0655 (0.483)	-0.0551 (-2.890)	0.134 (1.033)
Macroday	0.418 (2.980)	-1.242 (-1.307)	0.498 (3.353)	-0.739 (-0.743)	0.445 (3.069)	-1.308 (-1.372)
N Obs	65,119	10,668	72,136	9,785	78,051	10,642
Adj R2	0.072	0.189	0.090	0.188	0.087	0.189

Panel D: Raw Return in Excess of Market

Regime	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.104 (11.73)	0.0481 (0.967)	0.122 (13.93)	0.0567 (1.088)	0.114 (13.37)	0.0449 (0.902)
SUE*Macroday	-0.0540 (-2.875)	0.147 (1.147)	-0.0633 (-3.237)	0.0971 (0.724)	-0.0528 (-2.761)	0.160 (1.253)
Macroday	0.391 (2.766)	-1.113 (-1.184)	0.427 (2.886)	-0.652 (-0.663)	0.359 (2.483)	-1.169 (-1.241)
N Obs	65,694	10,822	78,726	9,927	84,332	10,795
Adj R2	0.072	0.126	0.083	0.131	0.081	0.127
Constant	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y

Table A1.9. Alternative Timing of Macroday

This table presents the effects of macroeconomic announcements on investor private information when earnings are announced one day after macroeconomic announcements. The dependent variable in all columns is *InvestorPI Alt*, investor private information measured by $CAR(ecd+1,-2)$, where “ecd” is the date of forming earnings consensus for a firm by I/B/E/S and CAR is the cumulative abnormal return generated via alternative models. *PostMacroday* equals 1 if earnings are announced one day after macroeconomic announcements, and 0 otherwise. Main explanatory variables and covariates are defined in Table 2. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fama-French 3-Factor		Carhart 4-Factor		CAPM		Market Model		Excess Market Return	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.0799 (9.161)	-0.00277 (-0.0713)	0.0797 (8.893)	0.00438 (0.101)	0.0839 (9.569)	0.0262 (0.667)	0.0781 (10.14)	0.0261 (0.669)	0.0781 (10.43)	0.0290 (0.749)
SUE *PostMacroday	-0.0657 (-3.290)	0.185 (1.531)	-0.0727 (-3.544)	0.203 (1.554)	-0.0646 (-3.234)	0.137 (1.107)	-0.0331 (-1.851)	0.164 (1.335)	-0.0331 (-1.839)	0.143 (1.180)
PostMacroday	0.560 (3.607)	-1.189 (-1.320)	0.562 (3.518)	-1.593 (-1.633)	0.618 (3.981)	-1.306 (-1.427)	0.273 (1.980)	-1.477 (-1.629)	0.257 (1.860)	-1.103 (-1.233)
N Obs	78,235	10,668	78,235	10,668	78,235	10,668	78,235	10,668	85,264	10,822
Adj R2	0.421	0.177	0.435	0.221	0.415	0.192	0.075	0.130	0.069	0.120
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A1.10. Alternative Timing of Macroday: Mitigating Concerns

This table presents the effects of macroeconomic announcements on pre-earnings-announcement drifts when earnings are announced one day after macroeconomic announcements. The dependent variable in all columns is *InvestorPI Alt*, investor private information measured by $CAR(ecd+1,-2)$, where “ecd” is the date of forming earnings consensus for a firm by I/B/E/S and CAR is the cumulative abnormal return generated using Fama-French 3-factor model. *PostMacroday* equals 1 if earnings are announced one day after macroeconomic announcements, and 0 otherwise. Main explanatory variables and covariates are defined in Table 2. Columns (1) and (2) exclusively include the observations in the post-Reg FD regime, columns (3) and (4) exclude observations of firms ever involved with illegal insider trades, and columns (5) and (6) exclusively include the observations without analyst earnings forecasts issued after I/B/E/S forms a firm’s earnings consensus but still before the date of this firm’s actual earnings announcement. Standard errors are clustered at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly. The covariates and the interaction terms of *SUE* with covariates are included.

Regime	(1)	(2)	(3)	(4)	(5)	(6)
	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.0711 (8.152)	-0.00277 (-0.0713)	0.0829 (9.087)	-0.00623 (-0.154)	0.0795 (9.120)	-0.00310 (-0.0794)
SUE *PostMacroday	-0.0543 (-2.811)	0.185 (1.531)	-0.0776 (-3.773)	0.143 (1.111)	-0.0667 (-3.339)	0.178 (1.463)
PostMacroday	0.243 (1.625)	-1.189 (-1.320)	0.639 (3.995)	-0.855 (-0.904)	0.561 (3.612)	-1.130 (-1.248)
N Obs	65,119	10,668	72,136	9,785	78,051	10,642
Adj R2	0.411	0.177	0.421	0.175	0.420	0.178
Constant	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	Y	Y	Y	Y	Y	Y
FE Firm	Y	Y	Y	Y	Y	Y

Table A1.11. Bloomberg Readership and Macroeconomic Announcements

This table provides the regression results to support Figure A2. Following Ben-Rephael, Da and Israelsen (2017), the dependent variable AIA measures abnormal institutional investor attention based on data of Bloomberg readership for firm-news searching and reading activities via Bloomberg terminals. *PreMacroday_5*, ..., *PreMacroday_1* are time indicators during the [-5,-1] window relative to the date of macroeconomic announcements, and *PostMacroday_1*, ..., *PostMacroday_5* are time indicators during the [1,5] window. Column (1) presents OLS regression results with robust standard errors, column (2) further include firm-fixed effects with standard errors clustered at the firm level. Column (3) presents Probit regression results with standard errors clustered at the firm level. Year-, month-, and day-of-week- fixed effects are included in all columns. Indicator variable of earnings announcement date is included in all columns. Within the parentheses are t-statistics for columns (1) and (2), and z-statistics for column (3). Adjusted R-square is reported for columns (1) and (2) while pseudo R-square is reported for column (3).

VARIABLES	(1) AIA	(2) AIA	(3) AIA
PreMacroday_5	-0.00389 (-9.180)	-0.00387 (-10.18)	-0.0208 (-10.47)
PreMacroday_4	-0.00394 (-9.403)	-0.00393 (-10.85)	-0.0201 (-10.70)
PreMacroday_3	-0.00377 (-8.826)	-0.00377 (-10.59)	-0.0188 (-10.24)
PreMacroday_2	-0.00214 (-5.233)	-0.00215 (-5.804)	-0.0101 (-5.372)
PreMacroday_1	-0.000834 (-1.966)	-0.000816 (-2.142)	-0.00452 (-2.331)
PostMacroday_1	0.00240 (5.661)	0.00239 (6.236)	0.0132 (6.786)
PostMacroday_2	0.00436 (10.57)	0.00436 (11.48)	0.0224 (11.61)
PostMacroday_3	0.00271 (6.264)	0.00272 (7.111)	0.0138 (7.142)
PostMacroday_4	0.000463 (1.095)	0.000472 (1.179)	0.00268 (1.330)
PostMacroday_5	0.000591 (1.373)	0.000615 (1.505)	0.00228 (1.112)
Year FE	Y	Y	Y
Month FE	Y	Y	Y
DOW FE	Y	Y	Y
N Obj	3,321,308	3,321,308	3,321,308
Adj R2/Pseudo R2	0.029	0.224	0.0274

Table A1.12. Strategically Timing Macroday by Firm Management?

This table provides OLS regressions of earnings surprises, SUE, on Macroday and covariates for the whole sample in column (1), and for the subsamples of expansions and recessions in columns (2) and (3), respectively. Following Dellavignall and Pollet (2009), *SUE* is the 11 quantiles of standardized unexpected earnings where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. Main explanatory variables and covariates are defined in Table 2.

VARIABLES	(1) SUE	(2) SUE	(3) SUE
Macroday	-0.0258 (-0.912)	-0.0453 (-1.515)	0.142 (1.612)
SameDayEarnings	0.0724 (4.125)	0.0685 (3.843)	0.0898 (2.089)
Friday	-0.349 (-5.656)	-0.351 (-5.486)	-0.339 (-2.117)
InstitutionalOwnership	0.473 (6.946)	0.428 (6.096)	0.974 (5.560)
AnalystCoverage	0.151 (4.051)	0.130 (3.363)	0.252 (2.742)
StaleConsensus	0.00764 (2.183)	0.00738 (2.024)	0.0160 (1.539)
Size	0.0125 (0.962)	0.0184 (1.352)	-0.0124 (-0.439)
Turnover	0.00516 (0.552)	0.0121 (1.217)	-0.0346 (-1.628)
Momentum_3	1.048 (21.90)	1.041 (19.27)	0.927 (8.814)
Momentum_9	0.420 (14.43)	0.417 (13.66)	0.274 (3.459)
Constant	6.997 (406.4)	7.038 (396.6)	6.672 (164.9)
N Obs	88,908	78,240	10,668
Adj R2	0.018	0.017	0.021
Sample	All	Expansion	Recession

Table A1.13. Immediate Price Response with a Refined Sample

This table presents the effects of macroeconomic announcements on immediate price responses to earnings news. The dependent variable is the two-day cumulative Fama-French 3-factor abnormal return. Main explanatory variables and covariates are defined in Table 2. Columns (1) and (2) cover full sample from 1998 to 2017 while columns (3) - (6) conduct subsample analyses of observations during expansions and recessions, accordingly. Observations with earnings news announced on NonMacroday but one day before Macroday are removed as robustness check. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly.

VARIABLES	CAR(0,1)	CAR(0,1)	CAR(0,1)	CAR(0,1)	Scaled CAR(0,1)	Scaled CAR(0,1)
	All		Expansion	Recession	Expansion	Recession
SUE	0.819 (54.77)	0.870 (45.99)	0.838 (43.74)	1.325 (13.62)	0.110 (43.74)	0.131 (13.62)
SUE*Macroday	0.0661 (2.279)	0.0759 (2.416)	0.0861 (2.720)	-0.0376 (-0.173)	0.0113 (2.720)	-0.00370 (-0.173)
Macroday	0.443 (2.037)	-0.509 (-2.123)	-0.580 (-2.415)	0.345 (0.206)	-0.0759 (-2.415)	0.0339 (0.206)
SameDayEarn	0.230 (2.207)	0.368 (2.645)	0.367 (2.619)	0.226 (0.306)	0.0480 (2.619)	0.0222 (0.306)
Friday	0.552 (1.562)	0.930 (2.260)	1.145 (2.699)	-0.597 (-0.290)	0.150 (2.699)	-0.0588 (-0.290)
InstitutionalOwn	-2.547 (-6.717)	-1.690 (-3.045)	-1.237 (-2.212)	-1.169 (-0.359)	-0.162 (-2.212)	-0.115 (-0.359)
AnalystCoverage	-0.538 (-2.410)	-1.189 (-4.146)	-1.245 (-4.233)	-1.751 (-1.257)	-0.163 (-4.233)	-0.172 (-1.257)
StaleConsensus	-0.0592 (-2.017)	-0.0880 (-2.639)	-0.106 (-3.111)	0.0329 (0.153)	-0.0138 (-3.111)	0.00324 (0.153)
Size	0.446 (6.368)	-0.362 (-3.097)	-0.379 (-3.124)	-0.417 (-0.741)	-0.0496 (-3.124)	-0.0410 (-0.741)
Turnover	-0.146 (-2.582)	-0.0976 (-1.518)	-0.0579 (-0.830)	-0.211 (-0.764)	-0.00757 (-0.830)	-0.0208 (-0.764)
Momentum_3	-0.190 (-0.515)	-0.684 (-1.663)	-1.119 (-2.528)	-2.400 (-1.523)	-0.146 (-2.528)	-0.236 (-1.523)
Momentum_9	-0.875 (-3.965)	-1.000 (-3.888)	-1.178 (-4.217)	-3.962 (-3.176)	-0.154 (-4.217)	-0.390 (-3.176)
Constant	-7.536 (-66.57)	-9.017 (-11.16)	-8.886 (-11.64)	-10.71 (-12.43)	-0.986 (-9.872)	-0.949 (-11.19)
SUE*Covar	Y	Y	Y	Y	Y	Y
N Obs	70,400	70,400	61,755	8,645	61,755	8,645
Adj R2	0.106	0.175	0.183	0.185	0.183	0.185
Standard Errors	Robust	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	N	Y	Y	Y	Y	Y
FE Firm	N	Y	Y	Y	Y	Y

Table A1.14. Immediate Price Response with a Refined Sample: Mitigating Concerns

This table presents the effects of macroeconomic announcements on immediate price responses to earnings news. The dependent variable is the two-day cumulative Fama-French 3-factor abnormal return. Main explanatory variables and covariates are defined in Table 2. Observations with earnings news announced on NonMacroday but one day before Macroday are removed as robustness check. Concerns are mitigated as in Tables 7 – 9. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly.

Regime	Post Reg FD		Remove IIT		Remove PCF	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
SUE	0.878 (41.68)	1.325 (13.62)	0.851 (53.46)	1.187 (17.28)	0.837 (43.67)	1.323 (13.59)
SUE*Macroday	0.0711 (2.097)	-0.0376 (-0.173)	0.0607 (2.251)	0.171 (1.090)	0.0869 (2.740)	-0.0357 (-0.164)
Macroday	-0.493 (-1.940)	0.345 (0.206)	-0.292 (-1.444)	-0.625 (-0.537)	-0.589 (-2.448)	0.326 (0.194)
SameDayEarn	0.435 (2.867)	0.226 (0.306)	0.231 (1.727)	-0.403 (-0.636)	0.363 (2.592)	0.259 (0.349)
Friday	1.298 (2.788)	-0.597 (-0.290)	0.886 (2.311)	-0.892 (-0.464)	1.133 (2.660)	-0.596 (-0.289)
InstitutionalOwn	-0.922 (-1.461)	-1.169 (-0.359)	-1.109 (-2.213)	0.125 (0.0425)	-1.221 (-2.179)	-1.293 (-0.397)
AnalystCoverage	-1.412 (-4.333)	-1.751 (-1.257)	-1.217 (-4.486)	-1.148 (-0.908)	-1.250 (-4.245)	-1.750 (-1.252)
StaleConsensus	-0.0796 (-2.126)	0.0329 (0.153)	-0.0668 (-2.476)	-0.134 (-1.010)	-0.107 (-3.152)	0.0240 (0.111)
Size	-0.608 (-4.261)	-0.417 (-0.741)	-0.388 (-3.484)	-0.665 (-1.275)	-0.376 (-3.100)	-0.402 (-0.713)
Turnover	-0.0518 (-0.682)	-0.211 (-0.764)	-0.121 (-1.882)	-0.240 (-0.981)	-0.0612 (-0.879)	-0.200 (-0.725)
Momentum_3	-1.543 (-2.902)	-2.400 (-1.523)	-1.425 (-3.528)	-2.975 (-2.204)	-1.128 (-2.549)	-2.401 (-1.520)
Momentum_9	-1.826 (-5.874)	-3.962 (-3.176)	-0.921 (-3.692)	-3.150 (-2.879)	-1.170 (-4.178)	-3.970 (-3.179)
Constant	-10.40 (-30.76)	-10.71 (-12.43)	-9.516 (-11.72)	-9.624 (-14.25)	-8.825 (-11.37)	-10.72 (-12.44)
SUE*Covar	Y	Y	Y	Y	Y	Y
N Obs	50,395	8,645	72,133	9,785	61,623	8,628
Adj R2	0.190	0.185	0.187	0.174	0.183	0.185
Standard Errors	Robust	Clustered	Clustered	Clustered	Clustered	Clustered
FE YYYYQ	N	Y	Y	Y	Y	Y
FE Firm	N	Y	Y	Y	Y	Y

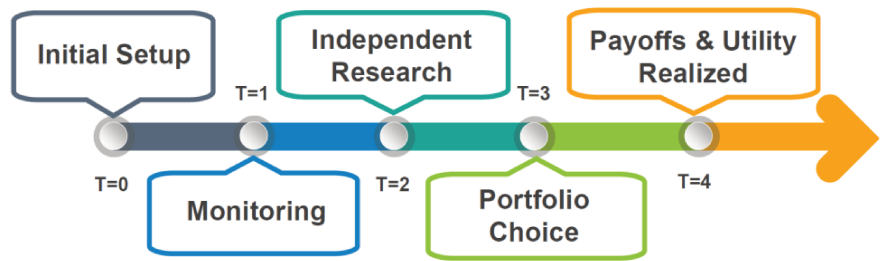
Table A1.15. Firm Earnings Announcements and Macroeconomic Announcements

This table presents conditional regression results exclusively using observations on Macrodaily. The dependent variable in all columns is immediate price response, CAR(0,1). MktRet is the value-weighted market return from CRSP daily return data. Main explanatory variables and covariates are defined in Table 2. Columns (1) and (2) cover full sample from 1998 to 2017 while columns (3) and (4) use subsamples of observations during expansions and recessions, respectively. Column (1) uses robust standard errors, and columns (2) – (4) cluster standard errors at the firm level. Within the parentheses are t-statistics. Time fixed effects and firm fixed effects are included accordingly.

Variables	CAR(0,1)	CAR(0,1)	CAR(0,1)	CAR(0,1)
	All		Expansion	Recession
SUE	0.871 (34.34)	0.947 (28.64)	0.930 (27.76)	1.998 (3.490)
SUE*MktRet	-2.804 (-1.438)	-2.077 (-0.884)	-3.446 (-1.370)	-0.119 (-0.00984)
MktRet	29.32 (2.032)	24.89 (1.398)	27.16 (1.389)	36.63 (0.387)
SameDayEarnings	0.646 (3.557)	0.374 (1.409)	0.478 (1.813)	-1.543 (-0.559)
Friday	1.227 (2.502)	1.088 (1.692)	0.982 (1.492)	-2.015 (-0.344)
InstitutionalOwnership	-3.207 (-5.044)	-1.479 (-1.385)	-1.167 (-1.074)	7.954 (0.611)
AnalystCoverage	-0.335 (-0.898)	-1.207 (-2.377)	-1.361 (-2.494)	-1.590 (-0.363)
StaleConsensus	0.0316 (0.594)	-0.0607 (-0.913)	-0.0865 (-1.271)	-1.527 (-1.688)
Size	0.505 (4.349)	-0.282 (-1.273)	-0.331 (-1.419)	-2.607 (-1.175)
Turnover	-0.0597 (-0.604)	-0.0148 (-0.120)	0.0144 (0.110)	-0.308 (-0.281)
Momentum_3	-0.962 (-1.398)	-1.808 (-2.034)	-1.695 (-1.850)	-0.974 (-0.180)
Momentum_9	-0.631 (-1.531)	-1.197 (-2.278)	-1.377 (-2.491)	-2.986 (-0.700)
N Obs	21,623	21,623	19,224	2,399
Adj R2	0.120	0.204	0.216	0.214
Constant	Y	Y	Y	Y
Covariates	Y	Y	Y	Y
SUE*Covar	Y	Y	Y	Y
Standard Errors	Robust	Clustered	Clustered	Clustered
FE YYYYQ	N	Y	Y	Y
FE Firm	N	Y	Y	Y

Figure 2.1. Model Monitoring and Learning in a Rational Expectations Framework

Panel A: Model Timeline



Panel B: Monitoring and Independent Research

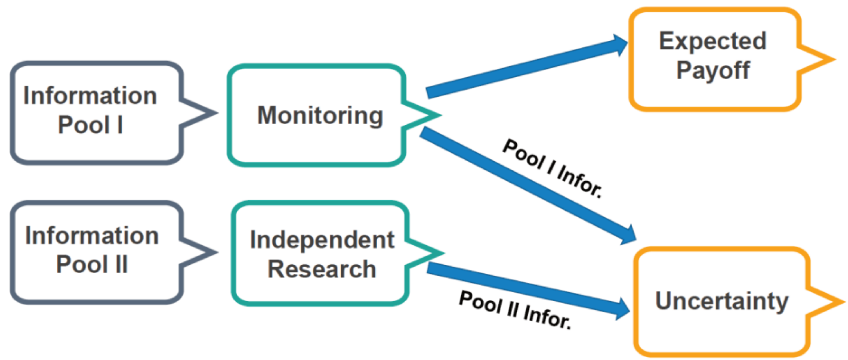


Table 2.1. Summary Statistics of Stock Picking Ability: Percentage Ownership

Stock picking ability is the main dependent variable. Regarding the within-portfolio evidence of percentage ownership in a portfolio firm by an individual institutional investor, summary statistics for three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. “Single Sort” and “Double Sort” correspond to the regression results in Table 3. Regarding the within-firm evidence in Table 4, summary statistics for three alternative measures of stock picking ability are presented in Panel D.

Panel A. Stock Picking Ability, Winsorized

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	138292	1.627	2.795	-8.294	-0.146	0.865	3.014	53.731
Double Sort	378980	1.568	3.105	-9.063	-0.319	0.63	2.926	59.03

Panel B. Stock Picking Ability, Bounded

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	138292	1.003	1.967	-8.294	-0.237	0.567	2.024	9.692
Double Sort	378980	0.802	1.952	-9.063	-0.393	0.385	1.833	9.286

Panel C. Stock Picking Ability, Raw

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	138292	21.937	1551.6	-8.294	-0.121	0.963	3.647	5.03E+05
Double Sort	378980	31.219	2700.6	-9.063	-0.31	0.671	3.369	1.08E+06

Panel D. Summary Statistics for Alternative Measures of Stock Picking Ability

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Winsorized	465070	1.905	3.412	-11	-0.533	1.169	3.565	50.571
Bounded	465070	0.78	1.906	-11	-0.563	0.681	1.928	11
Raw	465070	43.685	2896.445	-11	-0.533	1.231	4.406	8.49E+05

Table 2.2. Summary Statistics of Stock Picking Ability: Engagement Effectiveness

Stock picking ability is the main dependent variable. Regarding the within-portfolio evidence of an individual institutional investor's engagement effectiveness with a portfolio firm, summary statistics for three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. "Single Sort" and "Double Sort" correspond to the regression results in Table 5.

Panel A. Stock Picking Ability, Winsorized

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	111266	1.577	2.164	-7.917	0.282	1.096	2.262	56.677
Double Sort	274100	1.614	2.527	-8.465	0.088	1	2.451	62.187

Panel B. Stock Picking Ability, Bounded

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	111266	0.915	1.482	-7.917	0.09	0.615	1.353	9.5
Double Sort	274100	0.738	1.447	-8.465	0	0.521	1.273	9.364

Panel C. Stock Picking Ability, Raw

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	111266	25.284	1415.39	-7.917	0.305	1.241	3.099	3.56E+05
Double Sort	274100	27.429	1206.93	-8.465	0.098	1.06	3.099	2.69E+05

Figure 3.1. Reg FD as a Shock to Information Environment, 1995-1999 & 2001-2005

This figure presents the graphical relations between scores of stock picking ability and an institutional investor's percentage ownership in a firm. The vertical axis is the score of stock picking ability for an institutional investor, and the horizontal axis gives the five sorts of percentage ownership in a firm from *Low* to *High*. Blue bars are for the pre-2000 regime and grey bars for the post-2000 regime. *** indicates statistical significance at the 1% level for the difference between the pre-2000 and post-2000 levels within the same sort of percentage ownership.

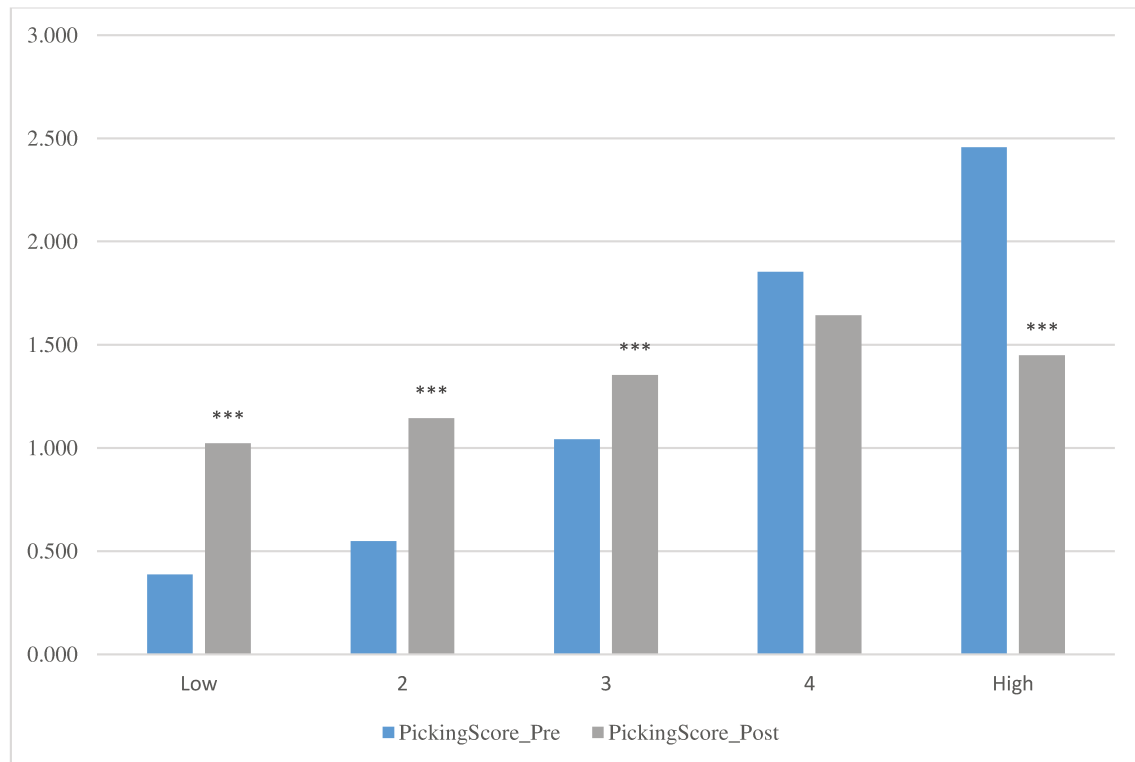


Table 3.1. Stock Picking Ability Sorted by Initial Holdings and Ex-ante Volatility

Horizontal sorting is based on an investor's initial holdings in a firm within her portfolio. Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low initial holdings. All columns absorb heterogeneity at the "investor by year-quarter" level.

Panel A. Stock Picking Ability, Winsorized

	Low Initial Holdings	High Initial Holdings	High - Low
	0.224	3.031	2.807***
Low Volatility	0.0196	2.887	2.867***
2	-0.0358	3.047	3.083***
3	-0.0490	3.154	3.203***
4	-0.0624	3.289	3.351***
High Volatility	-0.0176	3.446	3.464***

Panel B. Stock Picking Ability, Bounded

	Low Initial Holdings	High Initial Holdings	High - Low
	0.0208	1.985	1.964***
Low Volatility	-0.22	1.621	1.841***
2	-0.267	1.726	1.993***
3	-0.275	1.819	2.094***
4	-0.27	1.943	2.213***
High Volatility	-0.202	2.149	2.351***

Panel C. Stock Picking Ability, Raw

	Low Initial Holdings	High Initial Holdings	High - Low
	2.761	41.111	38.35*
Low Volatility	4.710	74.430	69.72
2	4.159	44.829	40.67***
3	2.282	53.302	51.02**
4	2.890	40.830	37.94***
High Volatility	2.712	82.052	79.34*

Table 3.2. Differentials of Stock Picking Ability among Investor Subgroups of a Firm

All institutional investors holding a given firm are sorted into five subgroups of initial holdings (IH), depending on their percentage holdings in this firm in the previous quarter. These five indicator variables are Low IH, IH_2, IH_3, IH_4, and High IH. A score of stock picking ability is calculated for each investor subgroup at the quarterly frequency. Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Statistical significance is relative to the score of stock picking ability for the “IH_3” subgroup. Column (1) uses robust standard errors; columns (2) and (3) cluster standard errors at firm level. Firm fixed effects are included in column (2), and fixed effects at “firm by year-quarter” level are included in column (3).

Panel A. Stock Picking Ability, Winsorized

VARIABLES	(1) Stock Picking Ability	(2) Stock Picking Ability	(3) Stock Picking Ability
Low IH	-3.701*** (0.00866)	-3.701*** (0.0227)	-3.685*** (0.0253)
IH_2	-2.706*** (0.00984)	-2.707*** (0.0234)	-2.699*** (0.0260)
IH_3	2.506*** (0.00791)	2.506*** (0.0123)	2.502*** (0.0137)
IH_4	1.297*** (0.0127)	1.297*** (0.0166)	1.297*** (0.0184)
High IH	2.070*** (0.0145)	2.070*** (0.0271)	2.070*** (0.0301)
Observations	465,070	465,070	465,070
R-squared	0.431	0.461	0.623

Panel B. Stock Picking Ability, Bounded

VARIABLES	(1) Stock Picking Ability	(2) Stock Picking Ability	(3) Stock Picking Ability
Low IH	-2.790*** (0.00582)	-2.789*** (0.0169)	-2.781*** (0.0189)
IH_2	-2.006*** (0.00647)	-2.006*** (0.0186)	-2.002*** (0.0207)
IH_3	1.574*** (0.00480)	1.574*** (0.00894)	1.572*** (0.00997)
IH_4	0.426*** (0.00687)	0.426*** (0.0125)	0.426*** (0.0139)
High IH	0.373*** (0.00675)	0.373*** (0.0145)	0.373*** (0.0162)
Observations	465,070	465,070	465,070
R-squared	0.490	0.517	0.657

Panel C. Stock Picking Ability, Raw

VARIABLES	(1) Stock Picking Ability	(2) Stock Picking Ability	(3) Stock Picking Ability
Low IH	-14.21*** (0.550)	-14.21*** (0.564)	-13.94*** (0.661)
IH_2	-11.58*** (0.592)	-11.57*** (0.601)	-11.45*** (0.691)
IH_3	13.14*** (0.548)	13.13*** (4.298)	13.06*** (4.775)
IH_4	26.37*** (3.793)	26.37*** (3.882)	26.37*** (4.324)
High IH	151.6*** (20.84)	151.6*** (21.04)	151.6*** (23.44)
Observations	465,070	465,070	465,070
R-squared	0.000	0.014	0.200

Table 3.3. Stock Picking Ability Sorted by Engagement Effectiveness and Ex-ante Volatility

Horizontal sorting is based on a firm's engagement effectiveness (EE) within her portfolio. Engagement effectiveness is measured with the scaled wealth-to-performance sensitivity in Edmans, Gabaix and Landier (2009). Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low engagement effectiveness, and all columns absorb heterogeneity at the "investor by year-quarter" level.

Panel A. Stock Picking Ability, Winsorized

	Low EE	High EE	High - Low
	1.562	1.593	0.0307***
Low Volatility	1.503	1.563	0.0600***
2	1.545	1.577	0.0315*
3	1.591	1.617	0.0262
4	1.627	1.693	0.0663***
High Volatility	1.663	1.758	0.0949***

Panel B. Stock Picking Ability, Bounded

	Low EE	High EE	High - Low
	0.918	0.914	-0.00434
Low Volatility	0.662	0.675	0.0128
2	0.687	0.694	0.00686
3	0.715	0.724	0.00862
4	0.758	0.778	0.0199**
High Volatility	0.821	0.871	0.0500***

Panel C. Stock Picking Ability, Raw

	Low EE	High EE	High - Low
	27.52	22.978	-4.542
Low Volatility	24.100	31.511	7.411
2	26.380	22.845	-3.535
3	24.510	18.187	-6.323
4	29.460	23.741	-5.719
High Volatility	48.390	25.150	-23.24

Table 3.4. Stock Picking Ability and Investor Distraction

As constructed in Kempf, Manconi and Spalt (2017), *Distraction* is the investor-specific component of firm-level distraction score. The dependent variable of Panel A is $PickingScore_{ijt}$, equal to the percentage change in the holdings of firm i by investor j at time t multiplied by the quintile of standardized earnings surprises of firm i for time $t+1$. The dependent variable of Panel B is d_PS_{ijt} , the first-order difference of $PickingScore_{ijt}$. Standard errors are clustered at firm level. Fixed effects are included accordingly at the level of firm, firm by year-quarter, investor by year-quarter, and firm by investor, respectively, for columns 2 to 5.

Panel A: Stock picking ability and investor distraction

VARIABLES	(1) PickingScore	(2) PickingScore	(3) PickingScore	(4) PickingScore	(5) PickingScore
Distraction	-0.387*** (0.0174)	-0.339*** (0.0270)	-0.373*** (0.0225)	-1.161*** (0.0707)	-0.446*** (0.0292)
Standard Errors	Robust	Clustered	Clustered	Clustered	Clustered
Firm FE	N	Y	N	N	N
Firm*YQ FE	N	N	Y	N	N
Investor*YQ FE	N	N	N	Y	N
Firm*Investor FE	N	N	N	N	Y
Observations	18,441,228	18,441,228	18,441,228	18,441,228	18,441,228

Panel B: Change in stock picking ability and investor distraction

VARIABLES	(1) d_PS	(2) d_PS	(3) d_PS	(4) d_PS	(5) d_PS
Distraction	-0.171*** (0.0250)	-0.188*** (0.0351)	-0.306*** (0.0306)	-0.354*** (0.0661)	-0.265*** (0.0405)
Standard Errors	Robust	Clustered	Clustered	Clustered	Clustered
Firm FE	N	Y	N	N	N
Firm*YQ FE	N	N	Y	N	N
Investor*YQ FE	N	N	N	Y	N
Firm*Investor FE	N	N	N	N	Y
Observations	18,441,228	18,441,228	18,441,228	18,441,228	18,441,228

Table 3.5. Contested Voting Activities at Annual General Meetings

A contested proposal is voted to either pass or fail by a 5% margin following Cuñat, Gine and Guadalupe (2012). Only the proposals with voting records at annual general meetings are summarized below. The sample period of this table covers 2002 – 2017.

Panel A. Contested Voting and Voting Outcomes

All Voted Proposals					
	Frequency	Percent			
Contested	1,622	0.91			
Uncontested	177,135	99.09			
Contested			Uncontested		
	Frequency	Percent		Frequency	Percent
Pass	776	47.84	Pass	169,808	95.86
Fail	846	52.16	Fail	7,327	4.14

Panel B. Contested Voting and Shareholder Proposals

All Voted Proposals			Shareholder Proposals		
	Frequency	Percent		Frequency	Percent
Management	170,532	95.40	Contested	781	9.50
Shareholder	8,225	4.60	Uncontested	7,444	90.50

Panel C. Management Recommendations

Shareholder Proposals			Management Proposals		
	Frequency	Percent		Frequency	Percent
Against	8,035	97.69	For	170,470	99.96
Others	190	2.31	Others	62	0.04

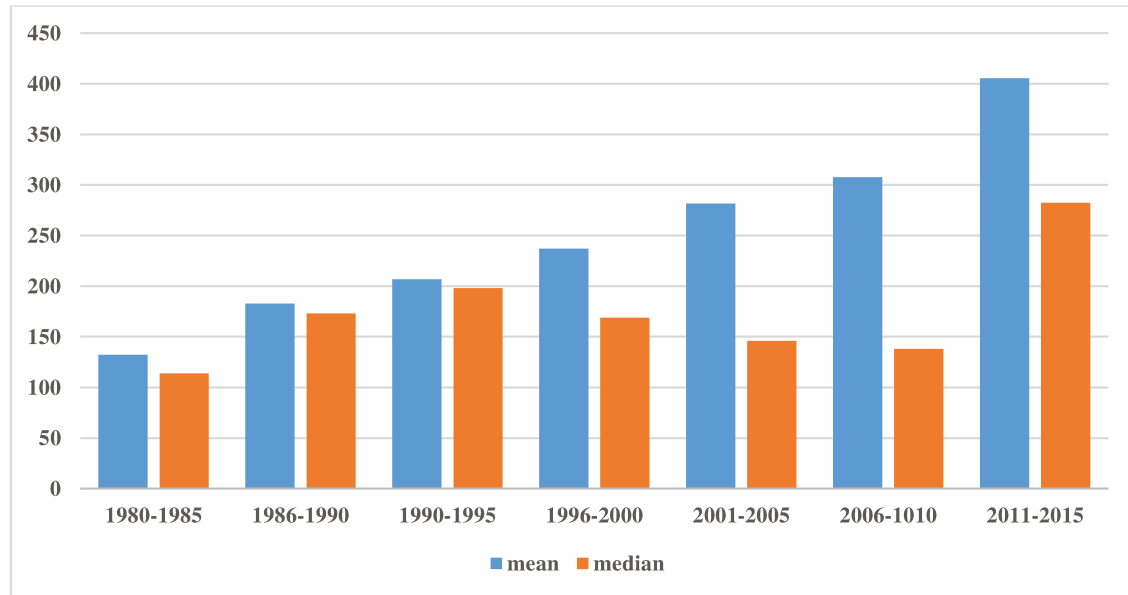
Table 3.6. Contested Annual General Meetings and Engagement Effectiveness

The binary dependent variable, *ContestMeeting*, takes the value of one if there are contested voting activities in a firm's shareholder-sponsored proposals at AGM, and zero otherwise. A contested proposal is defined following Cuñat, Gine and Guadalupe (2012). *ScaledWPS_sort* is a ranking variable based on the scaled wealth-to-performance sensitivity in Edmans, Gabaix and Landier (2009). *Distraction* is constructed as in Kempf, Manconi and Spalt (2017). Standard errors are clustered at firm level in columns (2) and (3). Year fixed effects are included in all columns. Control variables are defined in the appendix.

	(1)	(2)	(3)
MODELS	OLS	OLS	Probit
VARIABLES	ContestMeeting	ContestMeeting	ContestMeeting
ScaledWPS_sort	0.00590** (0.00236)	0.00590** (0.00224)	0.0236*** (0.00896)
Distraction	-0.380*** (0.138)	-0.380** (0.162)	-1.598** (0.706)
Mkt_cap	0.0156*** (0.00496)	0.0156* (0.00751)	0.0595** (0.0281)
Turnover	0.0106* (0.00572)	0.0106** (0.00419)	0.0400*** (0.0154)
Ret_q	-0.0695 (0.0425)	-0.0695 (0.0471)	-0.262 (0.192)
Momentum_9	-0.00720 (0.0253)	-0.00720 (0.0176)	-0.0305 (0.0710)
R_vol_q	-0.0399 (1.005)	-0.0399 (0.403)	-0.496 (1.413)
Constant	-0.0237 (0.0958)	-0.0898 (0.118)	-1.685*** (0.425)
Year FE	Y	Y	Y
Standard Error	Robust	Clustered	Clustered
Observations	2,882	2,882	2,882

Figure A3.1. Institutional Investors per Firm

Panel A: This figure presents the mean and median for the number of 13f institutional investors per firm among the largest 500 firms over the sample period from 1980 to 2015. Each quarter, I calculate market capitalization for each firm and select the largest 500 firms with available information regarding the number of 13f institutional investors.



Panel B: This figure presents the mean and median for the percentage ownership of the top-10 institutional investors per firm among the largest 500 firms over the sample period from 1980 to 2015. Each quarter, I calculate market capitalization for each firm and select the largest 500 firms with available information regarding the number of 13f institutional investors.

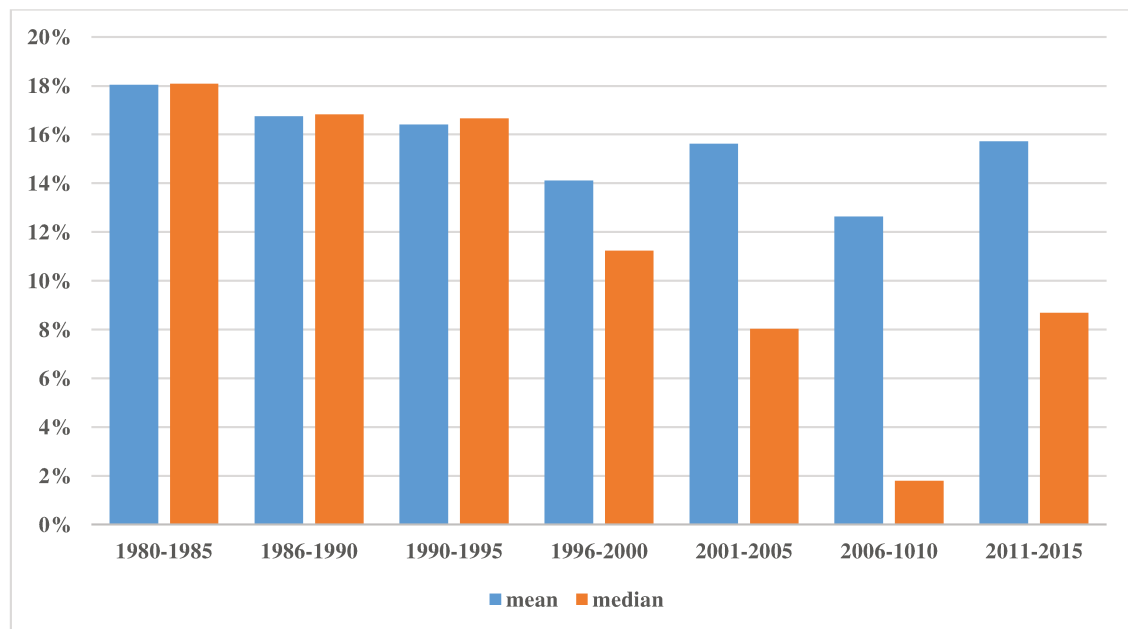


Figure A3.2a. Reg FD as a Shock to Information Environment, 1990-1994 & 2001-2005

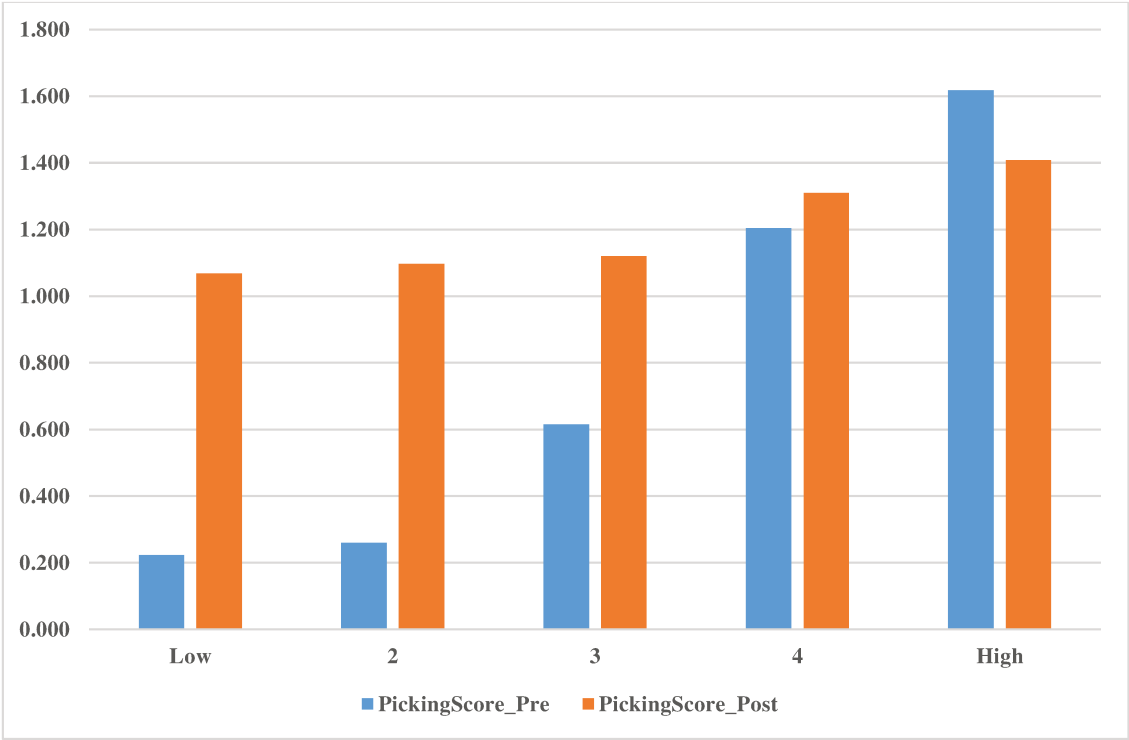


Figure A3.2b. Reg FD as a Shock to Information Environment, 1985-1989 & 2001-2005

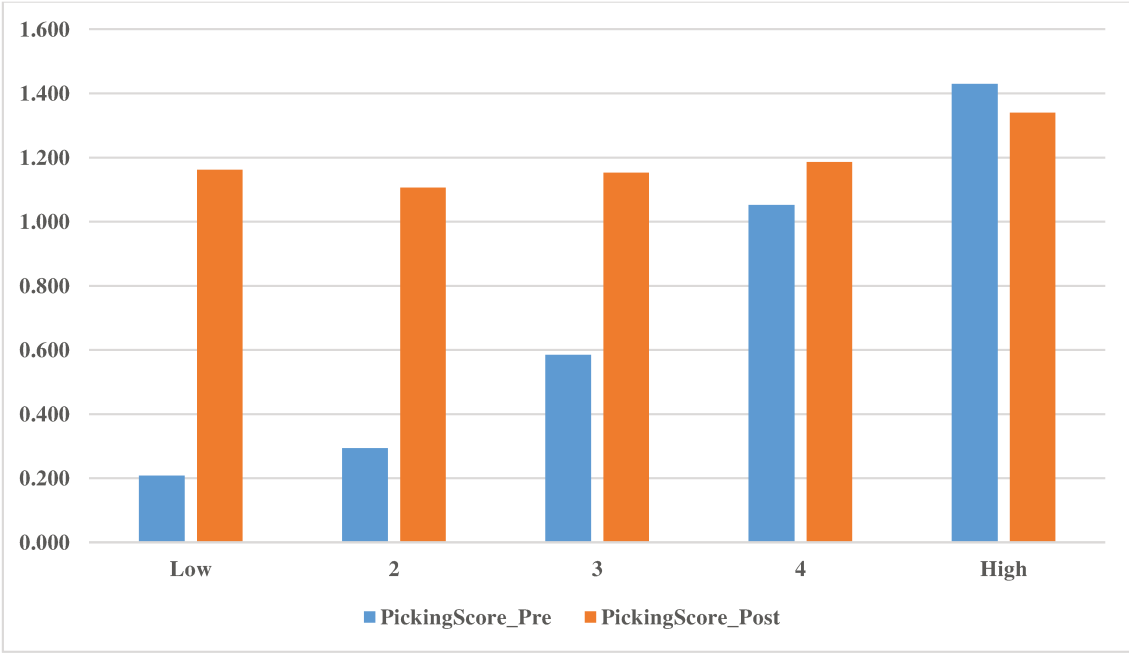


Figure A3.3. Composition of Institutional Investors: Number Count

This figure presents the composition of institutional investors based on Bushee's classifications of institutional investors. In Figure S1.a, institutional investors are classified as transient, dedicated, or index-tracking based on their portfolio diversification and investment horizon. Institutional investors are classified in Figure S1.b and Figure S1.c based on their fiduciary duties and their investment styles, respectively.

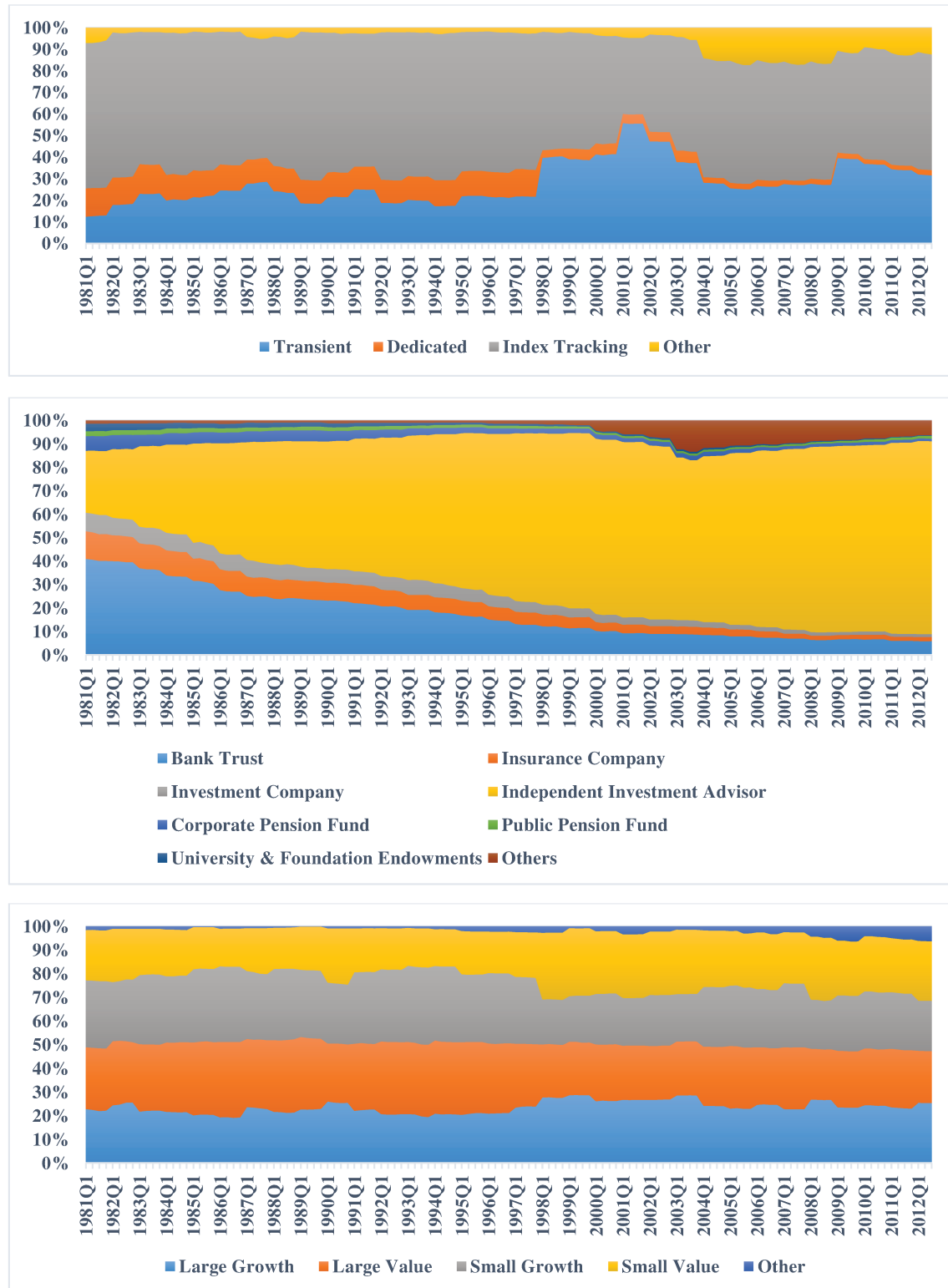


Figure A3.4. Composition of Institutional Investors: Market Capitalization

This figure presents the composition of institutional investors based on Bushee's classifications of institutional investors. In Figure S2.a, institutional investors are classified as transient, dedicated, or index-tracking based on their portfolio diversification and investment horizon. Institutional investors are classified in Figure S2.b and Figure S2.c based on their fiduciary duties and their investment styles, respectively.

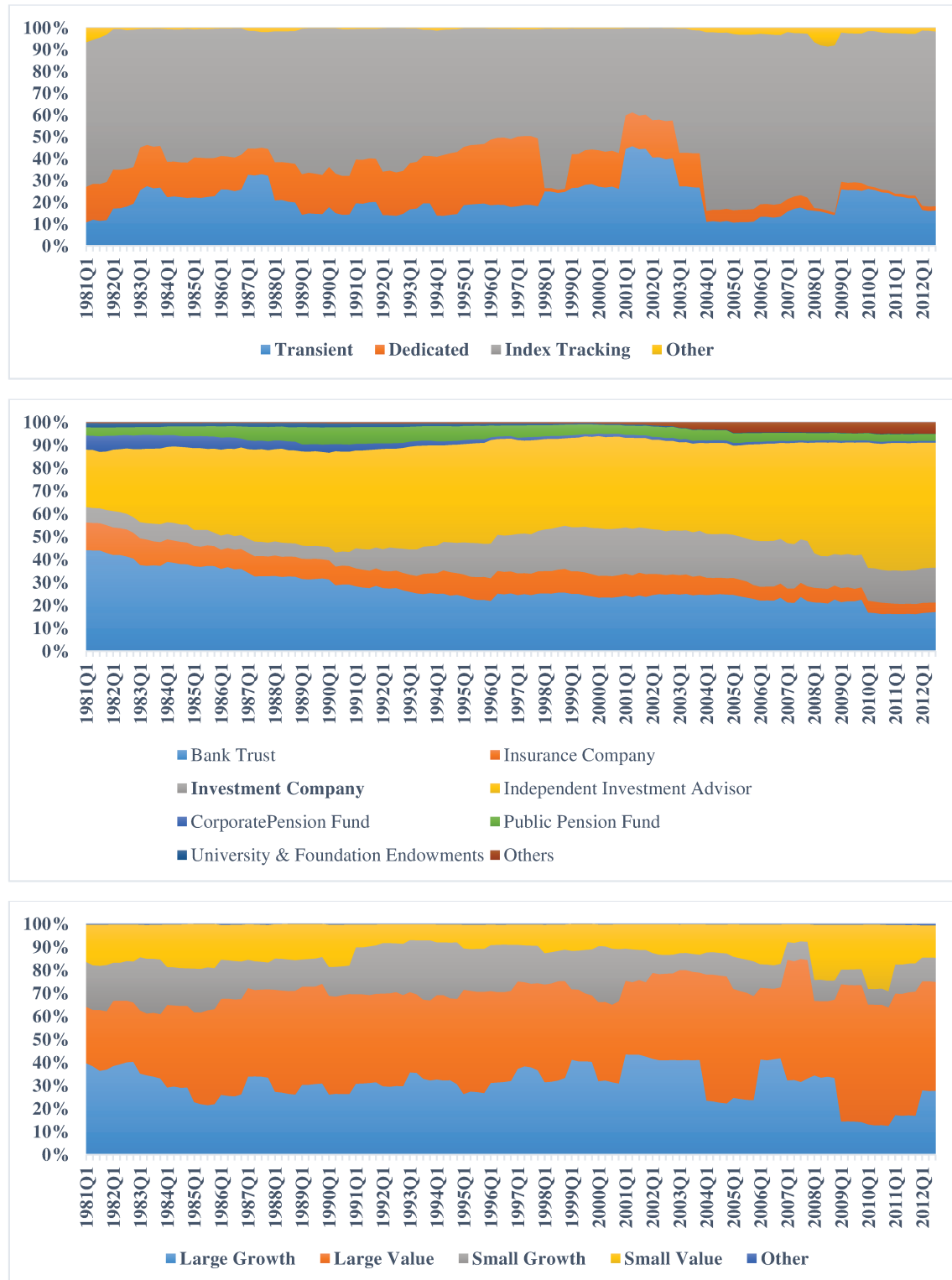


Table A3.1. Summary Statistics for Stock Picking Ability: CAR Excess Market

The table presents the summary statistics for an alternative measure of stock picking ability. Instead of using “SUE”, Stock Picking Ability can be measured as the covariance of percentage ownership in a portfolio firm with the cumulative abnormal return (CAR) over the next quarter. Quarterly CAR is measured as the holding period return in excess of the market return. Panels A and B are for the within-portfolio evidence and Panel C for the within-firm evidence.

Panel A. Stock Picking Ability by Initial Holdings

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	138262	0.887	4.762	-96.439	-0.536	0.155	1.775	129.24
Double Sort	378810	1.114	5.986	-209.538	-0.555	0.178	1.849	238.211

Panel B. Stock Picking Ability by Engagement Effectiveness

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Single Sort	111258	0.85	3.715	-69.46	-0.437	0.365	1.84	101.544
Double Sort	274250	1.07	4.77	-156.132	-0.496	0.347	2.044	160.548

Panel C. Stock Picking Ability by Initial Holdings: All Investors of a Firm

VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
W Ex Mkt	142560	1.246	5.308	-100.706	-0.483	0.411	2.261	139.756

Table A3.2. Stock Picking Ability: CAR Excess Market

The table replicates the main regressions regarding stock picking ability and percentage ownership in a firm at the previous quarter end. Instead of using “SUE”, Stock Picking Ability can be measured as the covariance of percentage ownership in a portfolio firm with the cumulative abnormal return (CAR) over the next quarter. Quarterly CAR is measured as the holding period return in excess of the market return. Panels A and B present the within-portfolio evidence corresponding to Tables 3 and 5. Panel C presents the within-firm evidence corresponding to Table 4.

Panel A. Stock Picking Ability: CAR Excess Market

	Low Initial Holdings	High Initial Holdings	High - Low
	0.176	1.599	1.423***
Low Volatility	0.123	0.938	0.815***
2	0.142	1.261	1.119***
3	0.186	1.710	1.524***
4	0.246	2.301	2.055***
High Volatility	0.573	3.659	3.086***

Panel B. Stock Picking Ability: CAR Excess Market

	Low EE	High EE	High - Low
	0.628	1.072	0.444***
Low Volatility	0.455	0.682	0.227***
2	0.602	0.875	0.273***
3	0.797	1.096	0.299***
4	0.99	1.481	0.491***
High Volatility	1.381	2.341	0.960***

Panel C. Stock Picking Ability: CAR Excess Market

VARIABLES	(1) Stock Picking Ability	(2) Stock Picking Ability	(3) Stock Picking Ability
Low IH	-1.726*** (-65.45)	-1.723*** (-36.31)	-1.724*** (-32.38)
IH_2	-0.950*** (-34.64)	-0.948*** (-24.78)	-0.948*** (-22.15)
IH_3	1.616*** (71.23)	1.612*** (41.03)	1.614*** (36.67)
IH_4	0.592*** (14.13)	0.592*** (7.784)	0.587*** (6.891)
High IH	0.287*** (4.936)	0.300** (1.982)	0.295* (1.735)
Observations	142,560	142,560	142,560
R-squared	0.026	0.087	0.332

Table A3.3. Stock Picking Ability and Initial Holdings in the Post-RegFD Regime

The table replicates Table 3 but exclusively using observations in the Post-RegFD regime. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low initial holdings. All columns absorb heterogeneity at the “investor by year-quarter” level.

Panel A. Stock Picking Ability, Winsorized

	Low Initial Holdings	High Initial Holdings	High - Low
	0.224	3.162	2.938***
Low Volatility	0.0135	3.061	3.047***
2	-0.0565	3.220	3.276***
3	-0.0636	3.324	3.388***
4	-0.0760	3.440	3.516***
High Volatility	-0.0202	3.591	3.611***

Panel B. Stock Picking Ability, Bounded

	Low Initial Holdings	High Initial Holdings	High - Low
	0.00413	2.078	2.074***
Low Volatility	-0.263	1.700	1.963***
2	-0.312	1.825	2.137***
3	-0.31	1.924	2.234***
4	-0.306	2.037	2.343***
High Volatility	-0.219	2.227	2.446***

Panel C. Stock Picking Ability, Raw

	Low Initial Holdings	High Initial Holdings	High - Low
	3.313	53.503	50.19
Low Volatility	5.874	102.694	96.82
2	5.097	59.727	54.63**
3	2.768	65.828	63.06*
4	3.550	56.29	52.74**
High Volatility	3.593	106.893	103.3

Table A3.4. Stock Picking Ability and Investor Subgroups in the Post-RegFD Regime

This table replicates Table 4 but exclusively using observations in the Post-RegFD regime. All institutional investors holding a given firm are sorted into five subgroups of initial holdings (IH), depending on their percentage holdings in this firm in the previous quarter. These five indicator variables are Low IH, IH_2, IH_3, IH_4, and High IH. A score of stock picking ability is calculated for each investor subgroup at the quarterly frequency. Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Statistical significance is relative to the score of stock picking ability for the “IH_3” subgroup. Column (1) uses robust standard errors; columns (2) and (3) cluster standard errors at firm level. Firm fixed effects are included in column (2), and fixed effects at “firm by year-quarter” level are included in column (3).

Panel A. Stock Picking Ability, Winsorized

VARIABLES	Stock Picking Ability	Stock Picking Ability	Stock Picking Ability
Low IH	-2.773*** (-136.2)	-2.771*** (-48.67)	-2.773*** (-43.52)
IH_2	-1.869*** (-86.44)	-1.868*** (-45.53)	-1.870*** (-40.66)
IH_3	1.755*** (101.1)	1.733*** (64.00)	1.737*** (57.31)
IH_4	1.996*** (67.21)	2.009*** (38.51)	1.999*** (34.25)
High IH	3.184*** (84.80)	3.282*** (29.12)	3.278*** (25.97)
N Obj	92,041	92,041	92,041
Adj R2	0.384	0.466	0.648

Panel B. Stock Picking Ability, Bounded

VARIABLES	Stock Picking Ability	Stock Picking Ability	Stock Picking Ability
Low IH	-2.263*** (-151.0)	-2.261*** (-48.96)	-2.258*** (-43.85)
IH_2	-1.483*** (-96.49)	-1.483*** (-42.32)	-1.483*** (-37.81)
IH_3	1.188*** (100.4)	1.176*** (65.63)	1.176*** (58.82)
IH_4	1.003*** (56.92)	1.010*** (30.66)	1.003*** (27.24)
High IH	1.183*** (66.98)	1.237*** (28.74)	1.239*** (25.68)
N Obj	92,041	92,041	92,041
Adj R2	0.432	0.510	0.686

Panel C. Stock Picking Ability, Raw

VARIABLES	Stock Picking Ability	Stock Picking Ability	Stock Picking Ability
Low IH	-10.52*** (-9.416)	-10.53*** (-8.178)	-10.70*** (-7.390)
IH_2	-8.174*** (-7.137)	-8.076*** (-6.697)	-8.159*** (-6.034)
IH_3	9.963*** (9.038)	9.638 (1.368)	9.760 (1.235)
IH_4	34.18*** (3.593)	34.50*** (3.101)	34.27*** (2.751)
High IH	123.4*** (4.385)	124.7*** (4.007)	124.6*** (3.565)
N Obj	92,041	92,041	92,041
Adj R2	0.001	0.029	0.253

Table A3.5. Stock Picking Ability and Engagement Effectiveness in the Post-RegFD Regime

This table replicates Table 5 but exclusively using observations in the Post-RegFD regime. Horizontal sorting is based on a firm's engagement effectiveness (EE) within her portfolio. Engagement effectiveness is measured with the scaled wealth-to-performance sensitivity in Edmans, Gabaix and Landier (2009). Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low engagement effectiveness, and all columns absorb heterogeneity at the "investor by year-quarter" level.

Panel A. Stock Picking Ability, Winsorized

	Low EE	High EE	High - Low
	0.224	3.162	2.938***
Low Volatility	1.557	1.593	0.0360*
2	1.595	1.600	0.00512
3	1.624	1.638	0.0139
4	1.65	1.693	0.0430**
High Volatility	1.699	1.755	0.0558***

Panel B. Stock Picking Ability, Bounded

	Low EE	High EE	High - Low
	0.00413	2.078	2.074***
Low Volatility	0.67	0.675	0.00500
2	0.708	0.696	-0.0124
3	0.728	0.729	0.000928
4	0.771	0.769	-0.00161
High Volatility	0.838	0.863	0.0250**

Panel C. Stock Picking Ability, Raw

	Low EE	High EE	High - Low
	3.313	53.503	50.19
Low Volatility	27.730	38.690	10.96
2	31.030	25.179	-5.851
3	28.010	21.024	-6.986
4	33.910	25.722	-8.188
High Volatility	50.110	27.840	-22.27

Table A3.6. Stock Picking Ability: CAR Excess Market in the Post-RegFD Regime

The table replicates Table S2 but exclusively using observations in the Post-RegFD regime. Instead of using “SUE”, Stock Picking Ability can be measured as the covariance of percentage ownership in a portfolio firm with the cumulative abnormal return (CAR) over the next quarter. Quarterly CAR is measured as the holding period return in excess of the market return. Panels A and B present the within-portfolio evidence corresponding to Tables 3 and 5. Panel C presents the within-firm evidence corresponding to Table 4.

Panel A. Stock Picking Ability: CAR Excess Market

	Low Initial Holdings	High Initial Holdings	High - Low
	0.0839	1.3109	1.227***
Low Volatility	0.107	1.107	1.000***
2	0.111	1.317	1.206***
3	0.14	1.586	1.446***
4	0.149	1.876	1.727***
High Volatility	0.359	2.821	2.462***

Panel B. Stock Picking Ability: CAR Excess Market

	Low EE	High EE	High - Low
	0.537	0.821	0.284***
Low Volatility	0.545	0.697	0.152***
2	0.639	0.834	0.195***
3	0.766	0.960	0.194***
4	0.824	1.175	0.351***
High Volatility	0.945	1.774	0.829***

Panel C. Stock Picking Ability: CAR Excess Market

VARIABLES	(1) Stock Picking Ability	(2) Stock Picking Ability	(3) Stock Picking Ability
Low IH	-1.580*** (-51.08)	-1.577*** (-33.12)	-1.579*** (-29.63)
IH_2	-0.898*** (-28.07)	-0.895*** (-22.55)	-0.895*** (-20.20)
IH_3	1.416*** (53.86)	1.409*** (35.47)	1.413*** (31.74)
IH_4	0.546*** (11.05)	0.548*** (7.687)	0.543*** (6.805)
High IH	0.387*** (5.262)	0.416*** (2.862)	0.405*** (2.480)
N Obj	92,041	92,041	92,041
Adj R2	0.024	0.083	0.318

Table A3.7. Stock Picking Ability Sorted by Portfolio Weight and Ex-ante Volatility

This table replicates Table 3 but using the weight of an investor's holdings in a firm out of the total market capitalization of all her holdings at the same quarter end. Horizontal sorting is based on this weights of a firm within her portfolio. Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low initial holdings. All columns absorb heterogeneity at the "investor by year-quarter" level.

Panel A. Stock Picking Ability, Winsorized

	Low Initial PortWgt	High Initial PortWgt	High - Low
	2.774	3.788	1.014***
Low Volatility	2.511	3.871	1.360***
2	2.6	4.047	1.447***
3	2.689	4.195	1.506***
4	2.829	4.358	1.529***
High Volatility	2.955	4.595	1.640***

Panel B. Stock Picking Ability, Bounded

	Low Initial PortWgt	High Initial PortWgt	High - Low
	2.185	2.186	0.000624
Low Volatility	1.7	1.827	1.360***
2	1.783	1.915	1.447***
3	1.882	2.013	1.506***
4	2.037	2.145	1.529***
High Volatility	2.245	2.408	1.640***

Panel C. Stock Picking Ability, Raw

	Low Initial PortWgt	High Initial PortWgt	High - Low
	22.45	81.24	58.79*
Low Volatility	16.43	79.94	1.360***
2	22	57.72	1.447***
3	15.24	52.97	1.506***
4	13.26	90.89	1.529***
High Volatility	17.85	103.69	1.640***

Table A3.8. Stock Picking Ability Sorted by Portfolio Weight and Ex-ante Volatility in the Post-RegFD Regime

This table replicates Table S7 but exclusively using observations in the Post-RegFD Regime. Horizontal sorting is based on this weights of a firm within her portfolio. Three alternative measures of stock picking ability are presented in Panels A, B, and C, respectively. Vertical sorting is based on realized volatility of daily return in the previous quarter. Statistical significance is for the differential in stock picking ability between high and low initial holdings. All columns absorb heterogeneity at the “investor by year-quarter” level.

Panel A. Stock Picking Ability, Winsorized

	Low Initial PortWgt	High Initial PortWgt	High - Low
	2.895	3.934	1.039***
Low Volatility	2.662	4.135	1.473***
2	2.751	4.345	1.594***
3	2.855	4.500	1.645***
4	2.987	4.623	1.636***
High Volatility	3.099	4.836	1.737***

Panel B. Stock Picking Ability, Bounded

	Low Initial PortWgt	High Initial PortWgt	High - Low
	2.279	2.278	-0.000858
Low Volatility	1.764	1.933	0.169***
2	1.887	2.057	0.170***
3	2.004	2.172	0.168***
4	2.149	2.290	0.141***
High Volatility	2.333	2.529	0.196***

Panel C. Stock Picking Ability, Raw

	Low Initial PortWgt	High Initial PortWgt	High - Low
	27.91	107.8	79.89*
Low Volatility	21.29	109.75	88.46*
2	30.18	73.93	43.75**
3	17.7	66.83	49.13***
4	17.19	119.69	102.5***
High Volatility	22.27	136.27	114.0**

Table A3.9. Contested Annual General Meetings and Engagement Effectiveness

The binary dependent variable, *MeetingContest*, takes the value of one if there are contested voting activities in a firm's shareholder-sponsored proposals at AGM, and zero otherwise. The main explanatory variable, *ScaledWPS_sort* is a ranking variable based on the scaled wealth-to-performance sensitivity in Edmans, Gabaix and Landier (2009). "Distraction" is constructed as in Kempf, Manconi and Spalt (2017). Standard errors are clustered at firm level in columns (2) and (3). Year fixed effects are included in all columns. Control variables are defined in the appendix.

	(1)	(2)	(3)
MODELS	OLS	OLS	Probit
VARIABLES	MeetingContest	MeetingContest	MeetingContest
ScaledWPS_sort	0.00590** (0.00236)	0.00590** (0.00218)	0.0237*** (0.00871)
Distraction	-0.511*** (0.151)	-0.511** (0.199)	-2.370** (1.003)
Mkt_cap	0.0157*** (0.00481)	0.0157* (0.00761)	0.0601** (0.0285)
Momentum	-0.0224 (0.0231)	-0.0224 (0.0138)	-0.0867 (0.0574)
Turnover_cumulative	0.0124** (0.00564)	0.0124*** (0.00390)	0.0460*** (0.0137)
IS	-0.0314 (0.0219)	-0.0314 (0.0190)	-0.157* (0.0874)
Year FE	Y	Y	Y
Standard Error	Robust	Clustered	Clustered
Observations	2,882	2,882	2,882