Imperial College London
Business School

Media Content and Credit Risk: Empirical Analyses Based on Credit Default Swap Market

Yining Shi

September 2016

Submitted in part fulfilment of the requirements for the degree of
Doctor of Philosophy in Business School of
Imperial College London

Abstract

This thesis aims to explore the impact of media content on credit risk by using the Credit Default Swap (CDS) and to investigate the Chinese real estate market. Chapter 1 provides the motivation and a detailed summary of this thesis. Chapter 2 focuses on the impact of government bailout news on systemic risk during the European sovereign debt crisis. A market-based systemic risk measure is proposed. The empirical results suggest that crisis interventions conducted by the European Central Bank (ECB) help to stabilise the financial and sovereign sectors, and the bailout actions from the International Monetary Fund (IMF) have a dominant effect on the non-financial sector. Chapter 3 explores the impact of media content on sovereign credit risk by using a news sentiment variable from the Thomson Reuters News Analytics database. The results show that such media tone contains both noise and new information, and has a significant influence on the sovereign CDS returns. Chapter 4 studies the impact of news sentiment on a firm's credit and equity risks. A firm-specific news sentiment is constructed via performing the linguistic analysis on news articles published by the Wall Street Journal. The equity market shows consistent superior reactions to the media sentiment. Furthermore, the impact of media content concentrates on the U.S. financial crisis period. The empirical findings support explanations related to the investor inattention theory. Chapter 5 shifts the focus to the Chinese real estate market and examines the relationship between credit supply and house prices. The financial deregulation process of China in opening up its local currency business to foreign banks is used to identify the impact of foreign credit. This deregulation expands the household credit supply and increases house prices. Meanwhile, provinces with higher participation rates of foreign banks experience larger house price depreciations during the financial crisis.

Contents

[1]This chapter is based on Cathcart, Gotthelf, Uhl, and Shi (2016).

List of Figures

List of Tables

Declaration of originality

I, Yining Shi, certify that this thesis titled, 'Media Content and Credit Risk: Empirical Analyses Based on Credit Default Swaps Market', constitutes my own work and that all material, which is not my own work, has been properly acknowledged. I confirm that:

- Chapter 2 of this thesis is a joint paper with Professor Enrico Biffis and Professor Pasquale Della Corte.

- Chapter 3 of this thesis is a joint paper with Professor Lara Cathcart, Nina Gotthelf and Matthias Uhl.

- Chapter 4 of this thesis is the joint work with Professor Lara Cathcart and Professor Lina El-Jahel.

Yining Shi

Copyright

Yining Shi

Acknowledgements

First of all, I am greatly indebted to my PhD supervisor, Professor Lara Cathcart, for her invaluable guidance in my study and helpful comments on my work. Her encouragement allows me to pursue what I am truly interested in. At the same time, her rigorous supervision makes sure I am on the right track. I am also deeply grateful to Professor Enrico Biffis for giving me the opportunity to work under his supervision at the early stage of my PhD, for providing me with intellectual inspiration, guidance and assistance over my PhD journey. My appreciation is extended to Professor Pasquale Della Corte, for his patient guidance, insightful and rigorous comments on my work.

Secondly, I would like to thank my PhD thesis examiners, Professor Alexander Michaelides, Professor Yongjun Tang for their invaluable comments and inspirations on my work.

I would also like to express my gratitude to Catherine Lester, Katherine Campbell and Moira Rankin for taking care the administrative aspects of my PhD; as well as to Lisa Umenyiora, Trace Andrew and other teaching faculty members for providing assistance with various teaching positions I have undertaken at Imperial.

My PhD study time at Imperial has been a cherishable experience. For this, I'd like to thank Silvia Diez-Gonzalez, Olga Bodero and Violeta Balinskaite. We were complete strangers 3 years ago. Now they are my big sisters and always take care of me, especially when I struggled in my research or in my personal life. I feel very embraced. Also I would also like to thank my master classmates Richard, Beini and Panyi for providing support in all the races and marathons I have taken part in over recent years. A friendship lasting 7 years means a lot to me. I would like to thank my PhD colleagues, Jialu and Hsuan, for the joy and time we spent together in the office.

I would like to give my heartfelt thanks to my parents, my grandparents and my younger brother for their unconditional love, support and encouragement in all my pursuits. The work presented in the thesis is dedicated to them.

To my parents, grandparents and my younger brother,
with love and admiration.

Chapter 1

Introduction

1.1 The Background

The first credit default swap (CDS) contract was introduced by J.P. Morgan in 1994, when the U.S. investment bank sold its credit risk exposure on the potential default of Exxon to the European Bank of Reconstruction and Development (Tett, 2009). After this, the CDS market grew spectacularly until the explosion of the U.S. subprime crisis in 2007. The crisis immediately led to the global meltdown in 2008, which contagiously caused the European sovereign debt crisis in 2010-2011. The CDS was heavily criticised in the global financial crisis for its contribution in creating the synthetic mortgage-backed securities (MBS), as well as the collateralised debt obligations (CDOs). The MBS (the same as the CDOs) provided cheap credits to the residential investment market (and to the real-estate developers), which facilitated to build the U.S. housing bubbles in 2006. These two financial products also complicate and transform the modern financial architecture into an intertwined network of financial obligations. Nevertheless, during the European sovereign crisis, the CDS was the tool used by investors to speculate potential government defaults, which artificially drove up the borrowing and funding costs for sovereigns (Augustin, Subrahmanyam, Tang, and Wang, 2014). The controversial role and usage of CDS in modern financial development have been widely debated in industry and academia. Despite this, the insurance cost of a CDS contract (i.e., CDS spread) has been widely used as a superior/pure measure of credit risk. For example, Longstaff, Mithal, and Neis (2005) use the information in CDS to obtain direct measures of credit risk in corporate yield spreads.

In this thesis, the CDS is used as the instrument that captures credit risk of the underlying entity. To provide the motivation, this chapter aims to provide an extent literature review on CDS. It starts with a brief introduction of the CDS contract definitions and conventions. It then introduces the CDS index, a multi-name credit product. This is the instrument used in Chapter 2 to study market systemic risk. Next, the nature of sovereign CDS and its differences from the corporate CDS are elaborated. Both Chapter 2 and 3 rely on a comprehensive data set of sovereign CDS. It then presents a discussion on the price discovery and information flow between the CDS market and the equity market. The special focus is placed on the role of news sentiment and media content. It is followed by a review of existing studies on the subjects of credit supply, house market and China.

1.2 The Credit Default Swap (CDS)

The concept of CDS is analogous to an insurance contract. It is a financial swap agreement, which allows the CDS buyer to purchase insurance against a contingent *credit event* on an underlying *reference entity*. To gain such protection, the CDS buyer needs to pay an *annuity premium* to the protection seller, who in return would compensate the buyer in the occurrence of a credit event with the amount of *loss given default (LGD)*. The annuity premium is termed as the *CDS spread*, which is defined as a percentage of the *notional amount* insured in basis points, and is paid quarterly or semi-annually over the life of a CDS contract. The *notional amount* is the face value of the bond (debt) issued by the reference entity that is insured with the CDS contract. Furthermore, the specific category of the entity's bond (debt) obligation, such as senior, unsecured, or junior, is defined in a CDS contract. According to the International Swaps and Derivatives Association (ISDA),[1] the definition of a *credit event* includes bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation/moratorium (for sovereign entities) and restructuring. The 2014 Credit Derivatives Definitions include a new credit event which is a government initiated bail-in action for financial reference entities.[2] The *loss given default (LGD)* paid by the protection seller in the case of a credit event is calculated as the difference between the insured notional principal and the value of the underlying reference obligation. The latter value is normally determined in the *credit event auction*, wherein the settlement format of the defaulted CDS contract is also decided by traders (i.e., a *cash settlement* or a *physical settlement*).

1.2.1 The CDS Index

The CDS market size, which is measured in terms of the gross notional amounts of CDS outstanding, was \$151 billion in 1997 (BBA, 2002) and reached \$62.2 trillion (ISDA, 2007) over a decade. According to the semi-annual survey of the Bank for International Settlements (BIS), the notional amounts of CDS contracts outstanding in December 2015 were \$12.3 trillion. A total of \$5.2 trillion were the CDS index products (i.e., multi-name CDS contracts). A CDS index is a basket of single-name CDS contracts on a list of constituents. Unlike a put option on the stock index, whose contract terminates immediately when the stock index falls below the exercise value, a CDS index contract continues to trade even if its underlying names default. It only terminates when all the constituent names default or when it matures. There are two classes of index products: the standard credit indices which are funded on the single-name bonds or CDS, and the synthetic structured indices such as the MBS and CDO. For the fully funded CDS indices, there are two main corporate credit derivative indices: the Markit iTraxx Europe Main and the Markit CDX North American Investment Grade. A

[1] ISDA (www.isda.org) plays a significant role in the development of credit derivative market. It involves in legal, legislation, contract design, trading convention aspects of the overall CDS market. For example, the ISDA Master Agreement and the 2003/2014 Credit Derivatives Definitions are crucial regulatory and legal documentations which build the foundations of today's CDS trading protocol.

[2] See http://www2.isda.org/asset-classes/credit-derivatives/2014-isda-credit-derivatives-definitions/

total of 125 European (American) investment-grade reference entities constitute the iTraxx Europe (CDX) credit index. Furthermore, 25 names of the 125 constitutions are financial corporates. In 2009, Markit issued several sovereign credit indices. For instance, the iTraxx SovX Western Europe includes the 15 most liquid sovereigns of Western Europe. The CDS index market is highly standardised with high liquidity flows. All CDS indices are reviewed every six months (i.e., 20 March and 20 September) with the release of a new on-the-run series.[3] The trading maturities contain one, two, three, five, seven and ten years. The coupon payments of CDS indices are standardised with 100 and 500 basis points. An upfront payment is used to settle any daily mark-to-market value. Under the Dodd-Frank Act, the U.S. Commodity Futures Trading Commission (CFTC) released a new regulation which demands for mandatory central clearing of CDS indices via a swap execution facility (SEF) in June 2013.[4] The introduction of central clearing, therefore, reduces the counterparty risk of CDS indices.

CDS index products are widely used in academic researches to study market liquidity risk and catastrophic systemic risk. This is because the market price of a CDS index always reflects investors' exceptions about default correlations or the likelihood of sector-wide joint default scenarios. Junge and Trolle (2015) study the price difference between a CDS index and its intrinsic theoretical value, where the latter is calculated via a portfolio of single-name CDSs on the index's constituents. The authors use the absolute value of such price wedge as a CDS market illiquidity measure based on ten different indices of the iTraxx and CDX families. In addition, Bhansali, Gingrich, and Longstaff (2008) adopt a linear model to explore the systemic risk component by using information from the CDX investment grade and high yield indices and their tranches. Their findings suggest that the dramatic increase of economic-wide risk during the U.S. subprime crisis is the main cause of increasing insurance cost of the credit indices.

1.2.2 The Sovereign CDS

If the late 1990s was a series of defaults from the developing economy sovereigns, then the late 2000s was an episode of sequential defaults from the advanced economies.[5] Unlike a corporate CDS, a sovereign CDS insures against the default of a sovereign or municipal government on its debt obligation. The credit event is normally a repudiation/moratorium instead of bankruptcy in the corporate CDS. Furthermore, a sovereign CDS is also exposed to currency risk. A currency depreciation (e.g., the Euro) normally follows its sovereign's default (e.g., Greece), which makes

[3]The previous releases are termed as off-the-run indices, and continue to be trade in the market.

[4]The full name of the act is *The Dodd-Frank Wall Street Reform and Consumer Protection Act*: http://www.cftc.gov/PressRoom/PressReleases/pr6607-13

[5]According to Reinhart and Rogoff (2009) and Standard & Pool's 2013 sovereign default study (Augustin, Subrahmanyam, Tang, and Wang, 2014), the following is a list of sovereign defaults since the 1998: Russia (1999), Pakistan (1999), Indonesia (1999, 2000, 2002), Argentina (2001, 2014), Paraguay (2003), Uruguay (2003), Grenada(2004, 2012), Venezuela (2005), Dominican Republic (2005), Belize (2005), Seychelles(2008), Ecuador (2008), Jamaica (2010), and Greece (2012).

the home-currency dominated CDS contract payment less attractive. Most importantly, the European sovereign credit crisis highlighted the critical usage of the sovereign CDS as a speculation tool, which led to a permanent ban on naked sovereign CDS trading issued by the E.U. in November 2012.

The literature has highlighted the importance of global risk factors being the main determinants of sovereign CDS spreads. Various studies confirm a strong factor structure in the co-movement among different sovereigns' CDS spreads over time.[6] Longstaff, Pan, Pedersen, and Singleton (2011) study the impact of various global, financial, regional and local risk factors on the sovereign credit risk by using CDS data on 26 countries. The authors decompose the sovereign credit risk into a default component and a risk premium component. They find that global risks such as U.S. equity risk, volatility risk premium and high yield spread, can significantly explain cross-sectional changes in the sovereign CDS spreads, and in the two risk premium components. Their findings are supportive of the work by Pan and Singleton (2008) on the sovereign risk premia of Korea, Mexico and Turkey. The credit risks of these three geographically different nations are significantly related to the VIX index, corporate investment spread and currency risk. Ang and Longstaff (2013) propose a sovereign CDS pricing model via the introduction of a common systemic risk factor and a country-specific risk factor. They examine the model with sovereign CDS data on the U.S. states and European countries. They find that the systemic risk factor is highly correlated with the U.S. financial market risk. Augustin and Tédongap (2016) provide alternative results that the two major principal components extracted from 38 countries' CDS term structures are strongly correlated to the U.S. consumption growth and macro-economic uncertainty. Dooley and Hutchison (2009) use 15 types of financial and real economic news from the U.S. and study the impact of news on the sovereign CDS spreads of 14 geographically dispersed countries. They found that during the subprime crisis period, the deteriorating economic and financial conditions in the U.S. had a statistically and economically significant impact on the emerging markets.

The recent European sovereign crisis was underlined by a series of government bailout actions. Various studies use CDS data to investigate the risk transfer mechanism of credit risk from the private sector to the public sovereign market via these crisis interventions. Acharya, Drechsler, and Schnabl (2014) suggest a two-way feedback effect between sovereigns and banks. That is, a government bailout directly reduces the CDS spreads on major banks that benefit from such intervention, while simultaneously increasing the sovereign CDS spreads. Meanwhile, the overloaded credit risk from the private sector dilutes the value of bank bailout guarantees and, conversely, affects the value of sovereign bonds. This risk spillover causes a strong co-movement in the CDS spreads of sovereigns and financial firms. Dieckmann and Plank (2012) document evidence that the pre-crisis state of a country's financial system is directly linked to the magnitude of the increase in European sovereign CDS spreads during the crisis period. Alter and Schüler (2012) study the interdependence of the

[6] E.g., Longstaff, Pan, Pedersen, and Singleton (2011); Billio, Getmansky, Gray, Lo, Merton, and Pelizzon (2014); Ang and Longstaff (2013); Pan and Singleton (2008); Augustin and Tédongap (2016); Remolona, Scatigna, and Wu (2008)

default risks between a Eurozone sovereign country and its domestic banking sector.[7] The authors observe a significant amount of default risk transfer from the banking sector to the sovereign market, channelled through the bank bailout programme. Furthermore, their sample focuses on the crisis period, and terminates before any financial rescue package released by the ECB, the IMF or the European Commission (EC). The work of Billio, Getmansky, Gray, Lo, Merton, and Pelizzon (2014) provides comprehensive statistical and econometric tools that can be used to precisely measure the risk spillover between the sovereign and banking sectors, such as the network analysis and the Granger causality coefficients.

1.2.3 News, Price Discovery between CDS and Equity Markets

The standard Merton (1974) structural framework treats a corporate's balance sheet as a series of contingent claims on the firm's asset. This establishes the direct linkage between a firm's equity value and the spread of a CDS contract which is underwritten on the firm's debt (i.e., the firm's debt is the obligation that underlies the CDS contract). If the market is efficient and frictionless, any information on the underlying firm should be reflected in both the equity and CDS markets. One branch of the information flow literature claims that there is a price discovery from the CDS market to the equity market. For example, Acharya and Johnson (2007) study a sample of 79 U.S. firms from 2001 to 2004 and find information flows from the CDS market to the equity market. However, such price discovery only occurs for firms that experience negative credit news and subsequent adverse shocks. Meanwhile, these firms tend to have closer relationships with the banks that issued them credit loans. The authors suspect such an information flow is caused by insider trading in the CDS market by the banks that have private information on the subjective firms. The latter study by Acharya and Johnson (2010) confirms the inside trading story via an empirical investigation on firms' leverage buyouts. Ni and Pan (2011) suggest that changes in CDS returns have a predicative power on stock returns over a few days. However, such a finding is based on the sample of stocks that experience short-sale bans. As a consequence, these bans forbid pessimistic investors to express their views in the equity market, and hence move to the CDS. Furthermore, the predictability is asymmetric and is mostly driven by the increases in CDS spreads.[8] The causal reverse relationship between the CDS and equity markets suggests that information flows move rather slowly.

On the other hand, another branch of the literature suggests that the price discovery direction is led by the equity market and followed by the CDS market. For example, Forte and Peña (2009) study the price discovery process among the stock, CDS and bond markets with a sample of 17 North American and European non-financial firms from 2001 to 2013. The empirical findings indicate that stock return is the primary market where new information is discovered. A further study by Norden and Weber (2009) examines the returns of 58 firms during 2000-2002 and finds similar results that

[7] These countries are France, Germany, Italy, Ireland, the Netherlands, Portugal and Spain.
[8] An increase in the CDS spread means negative information on the underlying.

the stock market leads the CDS and bond markets. Marsh and Wagner (2012) focus on the daily lead-lag relationship between the CDS and equity markets and draw the conclusion that the equity market precedes the CDS market in price discovery. Hilscher, Pollet, and Wilson (2015) document evidence that equity returns lead the CDS returns at daily and weekly frequencies. Furthermore, their findings suggest that informed traders prefer the equity market, while liquidity traders opt for the CDS market. The authors also find a significant delay in the CDS market towards the information released in the equity market. They link to the investor inattention explanation, which suggests that the liquidity traders in the CDS market pay less attention to news development, and hence are less updated with the news than informed traders in the equity market. This inattention theory also aligns with the findings by Norden and Weber (2004) that the CDS market reacts earlier than the equity market only on the downgrading rating news announcements. Norden (2009) provides further supportive evidence that high media coverage firms illustrate more significant reactions to rating downgrades announcements. However, a theoretical model proposed by Schweikhard and Tsesmelidakis (2012) suggests that the intensive government interventions during the European sovereign debt crisis depress the CDS spreads, and disconnect the information flow between the two markets. Furthermore, econometric analysis tools, such as Vector Autocorrelation (VAR) or Vector Error Correction Model (VECM), are widely used in this literature. These models allow researchers to capture linear interdependencies among multiple time series (VECM takes account of the co-integrated error terms).

1.3 Media Content and News Sentiment

Several studies have documented that the news sentiment, which is expressed in public documents, can forecast market returns. At an aggregate level, Tetlock (2007) is the first paper that finds news media content can predict future movements of the stock market. The author finds that negative sentiment in the news depresses returns. Tetlock, Saar-Tsechansky, and Macskassy (2008) extend the same framework to a micro firm level by studying the impact of negative words on firms' accounting earnings and stock returns. They conclude that the earning and return predictability from the negative words is the largest for news which has fundamentals-based stories. These two studies use the word classifications identified by the psychosociological Harvard-IV-4 TagNeg (H4N) Dictionary. The work of Loughran and McDonald (2011) applies sentiment analysis to the 10-K filings and designs their own Loughran and McDonald word list. Garcia (2013) studies the effect of news sentiment on assets prices from 1905 to 2005, and finds that the predictability of news content on stock returns is concentrated in recessions.

The causal relationship between news and asset prices is also explored in the literature. Dougal, Engelberg, Garcia, and Christopher (2012) use the rotation schedule of the Wall Street Journal as the exogenous fixed effects to identify a causal linkage between financial reporting and stock market performance. The significant unconditional effect of media content (measured as the fixed effects of individual journalists) suggests that the news sentiment has a causal effect on stock returns, rather than being just a reflection of investors' behaviours. Engelberg and Parsons (2011) further disentangle the causal impact of the content of the media reporting from the impact of the event itself. The authors use 19 mutually exclusive trading regions in the U.S. and study the reactions of local investors to an identical information event. They find local media coverage strongly predicts local trading, and that local trading is strongly related to the timing of local reporting.

Besides the stock market, various studies focus on the influence of news sentiment on the credit market (Tang and Yan, 2010, 2013; Cathcart, Gotthelf, Uhl, and Shi, 2016; Apergis, Lau, and Yarovaya, 2016). In particular, the study by Liebmann, Orlov, and Neumann (2016) constructs a dynamical corpus by using the capital return as a criterion to define the direction of a word (positive for increasing capital return, and negative for decreasing capital return). Such corpus is used to extract two news sentiment series: the corporate event news and the debt news. The authors find that both news sequences have significant effects on the CDS market, but only the corporate event news sequence impacts the equity market. The patterns of the two markets switch during the Great Recession.

1.4 Credit Supply, House Price and China

China, as the second largest nation around the world, has been the major engine for global economic growth during the past decade (Wei, Fang, Gu, and Zhou, 2015). As a Chinese, I'd like to use my knowledge and help to understand certain phenomena in China, such as the decade-long housing boom. Over the past thirty years, China has undergone a spectacular economic, sociological and demographic transformation, especially in its real estate market. Before the 1990s, China's urban housing sector was dominated by a housing provision system. Under this system, all urban housing units were built and owned by employers (work units) and allocated to individual households at low rents (Wu, Deng, and Liu, 2014). In 1998, the State Council issued the 23rd Decree, which eliminated the work units housing ownership and incorporated all previous implicit housing benefits into the employees' salaries. Such a reform led to a dramatic growth of the private housing market in China. Furthermore, because most households did not accumulate sufficient housing service during the provision system, this reform also led to a rapid expansion in urban housing demand (Wu, Gyourko, and Deng, 2012). The real estate investment to GDP was only 4 percent in 1999, which surged to 18 percent of GDP in 2014.[9] During the same period, China's average real house price tripled from 1508.6 Yuan per square meter in 1999 to 4467.1 Yuan per square meter in 2014.[10] In February 2011, the G-20 meeting explicitly pointed out that '*a potentially steep price correction in*

[9]China National Bureau of Statistics, based on the author's calculation.
[10]Yuan is the unit of local currency of China, which is Renminbi (RMB).

the Chinese property markets' as one major risk in the global recovery from the financial crisis.[11] Therefore, I'd like to investigate potential causes for such a dramatic rise of China's house price and generate useful policy application insights.

The importance of credit supply to house prices has been widely explored in the literature, especially after the U.S. subprime crisis (e.g., Adelino, Schoar, and Severino, 2012; Glaeser, Gottlieb, and Gyourko, 2013; Di Maggio and Kermani, 2015). For example, Mian and Sufi (2009) use ZIP code-level data and discover a salient feature of the mortgage default crisis. They find that mortgage defaults concentrate in subprime ZIP codes throughout the entire country. And it is the same subprime ZIP codes where experienced unprecedented relative growth in the mortgage credit from 2002-2005. Favara and Imbs (2015) suggest that the credit expansion, which is measured in terms of size and standard of a mortgage loan, boosts residential housing demands and pushes up the real estate prices. A recent paper by Tripathy (2015) uses the changes in Spain's banking regulation at 2012 as an exogenous shock to the household credit supply in Mexico, and study the corresponding impact of the decreased credit on real economic activities. The author finds that municipalities with higher shares of Spanish banks experience greater drops in the growth rate of household credit, and this leads to relatively larger drops in the lending to non-tradable production sectors of these municipalities.

The Chinese property market is perceived by investors as too-important-to-fail (Wei, Fang, Gu, and Zhou, 2015). Firstly, construction and real estates are the main sectors that boost local GDP and GDP performance is the main evaluation criterion for the local governor's career promotion. Such political motivation would cause both the central and local governments to actively engage in the housing market (Gao, Ru, and Tang, 2016; Qian and Roland, 1998). Secondly, since the 1994 fiscal reform, budget deficit has been a common fiscal pressure for local governments, who enjoy the monopoly power of urban land supply. Limited sources of public revenue lead local governments to rely heavily on land sales revenues to cover fiscal budgets. Unlike western countries, Chinese local governments have not been permitted to issue debt directly until recent. Hence, local governments establish the Local Government Financing Vehicles (LGFVs) by pledging lands and future land sales revenue as collateral. The LGFVs issue bonds based on these collaterals, and provide capital to local governments to fund large scale investments. A large drop in house prices or land prices would cause potential defaults of these LGFVs, which are backed by the local governments. Furthermore, house price is closely influenced by land price because real estate developers pay the costs to acquire the land usage rights. Given that local governments are highly engaged in land transactions, it is crucial to consider the roles of local governments and the costs of land when we study the house market movements. For example, Wu, Feng, and Li (2015) find that the local budget deficit ratio has a positive effect on land price.

[11]See: http://www.imf.org/external/np/g20/pdf/021811.pdf

1.5 Outline of the Thesis

Chapter 2 explores the impact of implicit and explicit bailout guarantees on the systemic risk, during the European sovereign credit crisis. A basket-index spread measure is constructed. It is calculated as the price difference of two insurance schemes: a basket of single-name CDSs on a list of constituents, and a CDS index which contains the same constituent names. The results show that such a spread measure helps to capture the systemic risks in the financial and sovereign sectors. During the global financial crisis, risk-averse investors worry about higher default correlations which may lead to a market collapse, and hence seek crash insurance via purchasing a CDS index contract. The surging demand for the crisis protection drives up the price of the CDS index, and depresses the basket-index spread. Government bailout actions, which successfully transfer the credit risk away from the financial (sovereign) sector, stabilise the price for the CDS index and increase the basket-index spread. This chapter examines the movement of the proposed systemic spread measure for the European non-financial, financial and sovereign sectors from 2006 to 2014. Firstly, the empirical results show that such a basket-index spread has a significant correlation with the first principal component of cross-sectional equity returns of the constituents. Secondly, it has negative correlations with the implied default correlation, the counterparty risk posed by CDS primary dealers, and global risk factors such as equity returns. Furthermore, these negative coefficients are of high statistical and economic significance. Thirdly, regression investigations confirm that the basket-index spread reacts positively to news announcements of affirmative fiscal and monetary crisis interventions by a variety of sources. In particular, bailout actions conducted by the ECB have significant impacts on the systemic risks of the financial and sovereign sectors, while IMF interventions affect the non-financial sector. Moreover, the highly persistent negative basket-index spreads favour a systemic risk story over a liquidity risk story. Robustness tests show that the spread has a significant prediction power on the option risk reversal and cross-sectional equity returns.

Chapter 3 studies the impact of media content on sovereign credit risk. In particular, this chapter aims to answer the question as to whether the media tone captures hard-to-quantify aspects of sovereign fundamentals. A specific media sentiment measure is constructed from the Thomson Reuters News Analytics (TRNA) database. The credit risk is extracted from an extensive set of sovereign CDS data. Furthermore, the decomposition is performed on the credit spread to get a risk premium component and a default risk component. This is conducted by using an affine credit valuation model. The empirical findings suggest that media tone explains and predicts sovereign CDS returns. The effect on the CDS and the default component returns partially reverses within five weeks whereas the effect on the risk premium reverses fully. Thus, it is reasonable to claim that the overall impact of news sentiment on CDS returns is a mixture of noise and new information. This is consistent with the prevailing theories of investor over- and underreaction. However, the noise signal appears to impact the risk premium and leads to a temporary change in investors' appetite for credit exposure. The information signal influences the default risk component and leads to a reassessment of the fundamentals of sovereign economies.

As an extension of Chapter 3, Chapter 4 examines the influence of news sentiment on the corporate credit risk. In particular, a firm-specific news sentiment variable is constructed by performing a linguistic textual analysis on news articles published by the Wall Street Journal from 2001 to 2016. Furthermore, for comparison, the news reaction of firms' equity returns is also examined in this chapter. The results show that the equity market responds to the firm-specific news much faster and stronger than the credit market. In addition, media news reports affect credit returns more significantly during the financial crisis period than the non-crisis period. During the financial crisis, the credit market also illustrates a significant amount of liquidity risk. The overall evidence supports the explanations related to the investor inattention theory. If a CDS trader has specific liquidity preferences, and if an investor's attention is a scarce resource, the CDS trader would pay less attention to news development as an informed equity trader. During the financial crisis when the liquidity risk is high, the CDS trader is forced to monitor market liquidity conditions by paying more attention to news development in order to avoid extreme losses.

Chapter 5 documents the impact of credit supply on the Chinese real estate market. The financial deregulation process of China in opening up its local currency (RMB) business to foreign banks from 1996 to 2006 is used to identify the impact of foreign credit. The liberalisation of RMB to foreign banks expands the credit supply to local residents and corporates. Furthermore, the U.S. financial crisis is defined as the event that exogenously reduces the household credit provisions in China. The variation of the exposures to the financial crisis across different provinces is used as a natural experiment to study the impact of credit supply on house prices. To measure the degree of financial liberalisation, the number of foreign banking institutions established inside the province by the end of 2006 is used. The reason year 2006 is chosen is because it is the year when the Chinese government removed all geographical and customs restrictions on foreign banks. A higher number of foreign banks indicate a larger provision of foreign capital, as well as a better overseas investment facility. The following hypotheses are examined in this chapter. First, house price is more expensive for a more financially liberalised province. Second, a province with a higher degree of financial openness also experiences larger price depreciation in its real estate market as evidenced during the 2008 financial crisis. In addition, the impacts of land price, public deficits, geographical constraints and other economic and fundamental factors are considered in the empirical investigation. This chapter also studies how credit supply influences land prices across the country. Because the supply of land is highly inelastic, and also because real estate price includes the cost of land, it is expected that the land price should react to credit expansion more intensively than the house price. Several interesting findings emerge. Firstly, the credit expansions, which are caused by the financial liberalisation, increase both the house and land prices. The impact on the land price is much larger than on the house price. Secondly, a more financially open province experiences more severe house price depreciation during the financial crisis, but not in its land price. One potential explanation is the 4 trillion RMB stimulus package issued by the Chinese central government in 2008, as well as the booming market of Local Government Financing Vehicles (LGFVs). Both facts contribute to large flows of cheap credit to the land market in 2008, leading to the appreciation of land prices. Thirdly, a province that is more geographically constrained (with less available land for construction usage) has higher property price. Furthermore, such geographical constraints intensify the additional house price drop in a financially liberalised province during the global crisis.

Chapter 2

Systemic Risk, Credit Default Swaps and Bailout Guarantees

2.1 Introduction

The question of how to accurately measure the systemic risk in the financial sector has been highlighted by the past financial crisis. It is one of the major challenges confronting regulatory, financial and economic communities. We propose a market-based systemic risk measure named the CDS basket-index spread.[1] Specifically, it uses the price difference between two identical insurance schemes: a portfolio of single-name CDS contracts on individual firms, and a CDS index constituting a list of the same firms. A portfolio of single-name CDS contracts provides protections to the CDS buyers against the defaults of any firms in that portfolio. A CDS index contract is the insurance contract on a portfolio of firms, and insures the buyer from any potential defaults of the index's constituents. As the two schemes provide investors with exactly the same payoffs, they should have the same price through the no-arbitrage argument. In practice, replication costs (such as transaction costs, regulation, liquidity and funding costs) typically make the first insurance scheme (i.e., the basket of single-name CDSs) more expensive than the second one (i.e., the CDS index), thus resulting in a positive basket-index spread.[2] However, the recent sovereign debt crisis was characterised by a large and persistently negative basket-index spread, especially for the financial sector. We propose a systemic risk explanation as follows. Risk-averse investors worry about potential market meltdown caused by increasing default correlations, and seek sector-wide crash protection by purchasing the CDS index products. The increasing demands for crisis protection products push up the cost of the CDS index relatively higher than the cost of its replicating basket, leading to a decreasing and negative basket-index spread. We investigate the dynamics of the basket-index spreads for the European non-financial, financial and sovereign sectors. Our measure of systemic risk has several merits. Firstly, it is a model-free risk measure. The time series for both the index and basket can be extracted directly from the Markit data source. If the investor prefers to construct the basket measure him/herself, it is also a text-book exercise with detailed steps listed by Markit. Secondly, the data is of high-frequency and allows users to construct intra-day trading strategy. Thirdly, the

[1]Note: In this chapter, spread stands for the 'basket-index spread' measure. To distinguish, we use phrases like 'insurance price, cost, premium' as the 'CDS spread'.

[2]See, for example, Markit Couderc (2007) and O'Kane (2011a) for a discussion of these issues.

measure is forward-looking by relying on the CDS index price. Fourthly, our measure can accurately capture the systemic sovereign risk of a region. Most systemic risk measures in the literature use equity prices, which would be problematic for the sovereign sector as it is difficult to measure the equity of a country precisely. Our basket-index spread measure would overcome such issues by using the CDS products and provide a comprehensive picture of regional sovereign systemic risk. Table 2.1 displays the summary statistics for the price of CDS index, CDS basket, and the basket-index spreads for all three sectors. The prices of both the insurance schemes increase during the European sovereign crisis, whereas the basket-index spread decreases. For example, the price of the financial sector CDS index increases from 84.05 basis points prior to the crisis to 185.74 basis points during the crisis. The replicating basket cost rises from 84.18 basis points to 186.56 basis points. However, the financial basket-index spread drops by 66 percent, from 3.04 basis points before the crisis to 1.04 basis points during the crisis. A similar movement pattern is observed in the sovereign CDS market.

Therefore, to confirm that the negative basket-index spread is a systemic risk measure, we investigate its relationship with four aggregate systemic risk measures suggested in the literature. For example, the autocorrelation coefficient and the principal component factors suggested by Billio, Getmansky, Lo, and Pelizzon (2012); the counterparty risk proposed by Schweikhard and Tsesmelidakis (2012) and Bai and Collin-Dufresne (2013); the risk-neutral correlation used in Kelly, Lustig, and Van Nieuwerburgh (2016) and Tarashev and Zhu (2008). First, we extract the time series of the first principal component that explains the cross-section variations in the constituents' equity returns, and study its relationship with the basket-index spread. We find a significant negative correlation between the two. Second, the results of a dynamic OLS regression suggest that the spread is significantly explained by the risk-neutral correlation implied by a CDS index, as well as the counterparty risk of the European CDS primary dealers. The empirical evidence indicates a strong linkage between the basket-index spread and traditional systemic risk variables. Third, we present a theoretical model to demonstrate how the increase in the aggregate risk (i.e., default correlation) influences the behaviour of our spread measure.

Meanwhile, the past financial crisis and Europe's sovereign debt crisis witnessed a series of government interventions originating from various authorities, including federal/regional governments and central banks. Effective and successful government bailouts substitute the systemic risk that would be suffered by the private sector, truncating extreme downside losses. The expectation of such implicit and explicit government bailouts by investors would depress the price of the crash insurance product (i.e., the CDS index) in the market, leading to an increasing basket-index spread. Therefore, if the proposed spread measure does indeed capture the systemic risk in the financial or sovereign sector, government announcements on bailout actions would have a significant influence on the spread movement. Any positive news on the government guarantee would increase the spread level as it helps to stabilise the insurance cost of the CDS index. On the other hand, any negative government news would decrease such spread measure further into the negative, since negative news intensifies risk-averse investors' demands for crash protections.

We collect the news articles published by the European Central Bank (ECB) and the International Monetary Fund (IMF). A linguist textual analysis is applied to these government announcements to study their sentiment directions. We use the standard bag-of-words textual analysis algorithm, which produces a sentiment score based on the number of positive and negative words inside the article. A positive score indicates active government interventions target the private (or sovereign debt) sector by bailing out troubled banks (or buying back government bonds), for example, the non-traditional operation of the Outright Monetary Transaction (OMT) conducted by the ECB in September 2012. A negative score suggests that the authorities are reluctant to intervene in the financially troubled banks (or sovereigns), which exposes investors to extreme downside losses. For example, the IMF and European Commission's decision on the Private Sector Involvement (PSI) of the Greek sovereign debt led to a restructuring default of the Greece sovereign CDS on the 9th March 2012 (Coudert and Gex, 2013). We perform regressions to study the impact of the government news score on the basket-index spread. We find that both news scores, based on the ECB and the IMF resources, have statistically significant effects on the spread. It confirms that a positive news announcement that contains affirmative bailout information reduces the CDS index's price and increases the basket-index spread, whereas a negative news announcement increases the CDS index price and causes a decreasing negative spread. Furthermore, we find that the ECB monetary operations are significant in mitigating the systemic risk in the financial and sovereign sectors, while the IMF policies have a dominant impact on the non-financial sector.

In addition, our findings align with previous literature that common risk factors have significant impacts on the sector-wide aggregate risk, such as the equity market return, the investment grade spread (Longstaff, Pan, Pedersen, and Singleton, 2011; Ang and Longstaff, 2013; Pan and Singleton, 2008) and the counterparty risk (Bai and Collin-Dufresne, 2013; Schweikhard and Tsesmelidakis, 2012). In particular, we find that these global and financial risk variables consistently influence the movement of the systemic spread measure. A series of robustness tests confirm that our findings are solid under difference empirical settings. Furthermore, the results indicate that the traditional liquidity risk story cannot fully explain the persistent non-zero negative basket-index spread over the sovereign crisis period nor does the arbitrage trading story. We perform the out-of-sample prediction regression, as well as the Fama-MacBeth cross-section asset pricing model to examine the explanatory power of our spread measure. The findings suggest that the spreads extracted from the financial and sovereign sectors can significantly predict the risk reversal in the option market. The systemic spread also illustrates considerable cross-sectional pricing power.

The chapter is organised as follows. Section 2.2 reviews the existing literature on the systemic risk and the CDS index products. This section also discusses studies on sovereign risk and government bailout interventions. Section 2.3 elaborates the construction of our basket-index spread. A brief theoretical model is demonstrated in section 2.4. Section 2.5 presents the preliminary empirical investigation on the spread as a systemic risk indicator. The investigation on the government news is discussed in section 2.6. Section 2.7 illustrates various robustness tests and section 2.8 concludes the chapter.

2.2 Related Literature

Our work contributes to the literature on systemic risk (e.g., Ang and Longstaff, 2013; Billio, Getmansky, Lo, and Pelizzon, 2012; Tarashev and Zhu, 2008; Adrian and Brunnermeier, 2016; Augustin and Tédongap, 2016; Bisias, Flood, Lo, and Valavanis, 2012). We provide a market systemic risk measure based on a CDS crash insurance product (e.g., Junge and Trolle, 2015; Kelly, Lustig, and Van Nieuwerburgh, 2016). It is also related to the literature on the role of implicit and explicit government interventions and monetary policies on financial system stability in dire economic conditions. In particular, we emphasise the credit risks in the financial and sovereign sectors and the spillover effect (e.g., Li, Li, and Yang, 2014; Billio, Getmansky, Gray, Lo, Merton, and Pelizzon, 2014; Geyer, Kossmeier, and Pichler, 2004; Kelly, Pástor, and Veronesi, 2016; Pástor and Veronesi, 2013; Schweikhard and Tsesmelidakis, 2012; Kallestrup, Lando, and Murgoci, 2016).

This paper contributes to the literature on measuring systemic risk in the financial and sovereign sectors, one of the major challenges faced by financial and regulatory communities.[3] The financial turmoil of 2007-2009 has motivated overwhelming academic and regulatory studies on systemic risk. The survey conducted by Bisias, Flood, Lo, and Valavanis (2012) provides a comprehensive review of 31 quantitative measures of systemic risk. The authors categorise these measures into four groups based on the techniques used: probability distribution measures; contingent-claims measures; illiquidity measures; network analysis measures and macroeconomic measures. This chapter focuses on the first two categories. The probability distribution measures are reduced-form measures of systemic risk, which study the joint distribution of defaults/losses of portfolios of systemically important financial institutions. For example, the CoVaR measure by Adrian and Brunnermeier (2016) is the value at risk (VaR) of the financial system, conditional on institutions being under stress (when the institutions' losses exceed the targeted VaR levels). The systemic expected shortfall (SES) proposed by Acharya, Pedersen, Philippon, and Richardson (2017), as well as the banking system multivariate density (BSMD) measure used by Segoviano Basurto and Goodhart (2009), follow a similar fashion by studying the joint distribution of assets returns. The contingent-claims and default measures follow the structural model by directly considering the balance sheet of a financial institution, in order to construct individual default probability. A joint default risk is then constructed by the assumption of multivariate distribution of returns (Lehar, 2005; Dale, Merton, and Bodie, 2009; Jobst and

[3]See Acharya, Drechsler, and Schnabl (2014); Kelly, Lustig, and Van Nieuwerburgh (2016); Kelly, Pástor, and Veronesi (2016); Adrian and Brunnermeier (2016); Acharya, Pedersen, Philippon, and Richardson (2017); Ang and Longstaff (2013); Longstaff, Pan, Pedersen, and Singleton (2011); Pan and Singleton (2008).

Gray, 2013; Huang, Zhou, and Zhu, 2009). We examine four aggregate systemic risk measures and link them to our basket-index spread. These four measures include the autocorrelation coefficient and the principal component factors suggested by Billio, Getmansky, Lo, and Pelizzon (2012); the counterparty risk proposed by Schweikhard and Tsesmelidakis (2012) and Bai and Collin-Dufresne (2013); the risk-neutral correlation used in Kelly, Lustig, and Van Nieuwerburgh (2016) and Tarashev and Zhu (2008).

In addition, we contribute to the literature on the sovereign credit risk in the light of the EU sovereign crisis. There is growing public consensus on sovereign credit risk and its impact on a nation's economy. Earlier literature uses syndicated loans (Boehmer and Megginson, 1990) or sovereign bonds (Mauro, Sussman, and Yafeh, 2002; Duffie, Pedersen, and Singleton, 2003; Geyer, Kossmeier, and Pichler, 2004; Cruces and Trebesch, 2013) to measure sovereign risk. More recent studies opt to employ CDS contracts to capture the sovereign credit risk (Duffie, Pan, and Singleton, 2000; Duffie and Singleton, 2003; Pan and Singleton, 2008; Zhang, 2008; Longstaff, Pan, Pedersen, and Singleton, 2011; Ang and Longstaff, 2013; Li, Li, and Yang, 2014). Sovereign CDS has merits over bonds for measuring the sovereign credit risk, thanks to the simplicity, standard clauses and terms of CDS contracts (Li, Li, and Yang, 2014), better liquidity conditions (Fontana and Scheicher, 2016), and less exposure to taxations (Beinstein, Sbityakov, Le, Goulden, Muench, Doctor, Granger, Saltuk, and Allen, 2006; Tomz and Wright, 2013). In terms of the theoretical model, several papers use a reduced-form approach to estimate the dynamics of sovereign default risk from CDS prices.[4] Pan and Singleton (2008) find that a common principal component explains more than 90% of the variations in Mexican, Turkish and Korean sovereign CDS spreads. Longstaff, Pan, Pedersen, and Singleton (2011) find that changes in CDS spreads across 26 countries are largely driven by common risk factors, such as the VIX index, the US equity return, and the high-yield corporate spreads. Ang and Longstaff (2013) isolate a systemic risk default intensity from sovereign-specific risk factors, based on the CDS spreads of the U.S. federal government and states, as well as 11 Euro Monetary Union (EMU) nations. They find that such systemic risk factor is linked to the U.S. financial market risk. An alternative approach to extract the sovereign default risk is the use of rating-based models.[5] Li, Li, and Yang (2014), for example, study 34 sovereign CDSs and discover similar results, that financial market variables (i.e., the VIX index and the MSCI stock index) drive variations in sovereign credit spread movements. They also find that the sovereign credit risk premium increases intensively during crisis periods, to a greater extent for CDS with higher ratings and longer maturities.

Our paper attempts to investigate the impact of sovereign risk and political uncertainty, caused by interventions, such as government bailouts, on financial system stability. In dire economic conditions, governments tend to bail out systemically important firms/financial intuitions to save the market from catastrophic losses. The losses that would be suffered by the private investors are partially

[4]See Duffie and Singleton (1999, 2003); Ang and Longstaff (2013); Longstaff, Pan, Pedersen, and Singleton (2011); Pan and Singleton (2008), for example.

[5]See Remolona, Scatigna, and Wu (2008); Li, Li, and Yang (2014); Farnsworth and Li (2007)

subsidised by the government's bailout and other rescue actions. Kelly, Lustig, and Van Nieuwerburgh (2016) show that crash insurance products, such as the put-of-the-money (OTM) put options on financial sector index, are underpriced during the financial crisis due to the market expectations of government bailouts for systematically important banks. A study by Acharya, Drechsler, and Schnabl (2014) finds that government bailout interventions transfer the credit risk in the private sector to the sovereign sector. The authors also suggest a feedback effect from the sovereign sector to the banking sector in the post-bailout period. Pástor and Veronesi (2012, 2013) discover that political uncertainty commands a risk premium in the stock market, and reduces the value of the implicit government put protection in terms of higher volatility risk and correlation risk among different assets. Billio, Getmansky, Gray, Lo, Merton, and Pelizzon (2014) measure and analyse the Granger-causality network interconnectedness between major banks and 10 EMU sovereigns. Their findings suggest that implicit and explicit government guarantees depress bank CDS spreads below where they would be in the absence of government support. In the post-bailout period, sovereign credit risk spills over to the financial sector.

2.3 The Measure: CDS Basket-Index Spread

This section starts with a brief description of credit indices, as well as the replication strategy to commence the index arbitrage. We then move onto the construction of the *basket-index spread* measure, and discuss its linkage with sector-wide systemic risk.

2.3.1 Credit Default Swap Indices: Description

A credit default swap index is an insurance instrument used by investors to protect against any defaults of the index's constituents. The name list of a credit index normally focuses on certain segments of the market. Credit indices are generally traded on the over-the-counter market with a fixed spread, a defined basket of reference entities, and with maturities ranging from one to ten years. The market of CDS indices is highly standardised and merits better liquidity conditions than the single-name CDS market.[6]

In order to gain protection against potential default of each constituent, an index protection buyer pays periodic premiums based on a fixed spread to the index protection seller. The notional amount of index is divided evenly among the index constituents. In the event of default, such as failure to pay, bankruptcy and restructuring, the protection seller compensates the protection buyer by paying the loss-given-default on the defaulted name. Afterwards, the notional amount of the index is reduced accordingly. In cases when the market spread of the index differs from the contract coupon,

[6] The average daily notional amount for the 1000 most actively traded single-name CDS is approximately 32 million USD, whereas the daily notional amount of untranched index transactions is about 800 million USD, according to the Market Activity Report published by the Depository Trust & Clearing Corporation (DTCC) in March 2014.

an upfront payment is required to ensure that the present value of the contract is zero.

For illustration, the 5-year iTraxx Sovereign Western Europe CDS Index (iTraxx SovX WE) has a fixed coupon of 100 basis points (bps) and has 15 constituents. A protection buyer who holds 10 million notional of the index delivers a premium on a quarterly basis with an amount of $\frac{1}{4} \times 0.0100 \times 10,000,000 = 25,000\ USD$ to the index protection seller. On 9 March 2012, the Greece sovereign CDS was delisted from the iTraxx SovX WE CDS index due to the restructuring of the Greek sovereign bond.[7] The protection seller compensates the losses suffered by the index protection buyer and pays $\frac{1}{15} \times 0.535 \times 10,000,000 = 356,667\ USD$, wherein 0.535 is the average loss of face value for bond holders of the defaulted Greek sovereign bond during this exchange. On the following periodic payment date (i.e., the 20th March 2012), the CDS premium payment is reduced to $\frac{1}{4} \times \frac{14}{15} \times 0.0100 \times 10,000,000 = 23,333\ USD$.

To ensure creditability and liquidity standards, the constituent list of the CDS index is revised every six months and a new series of each credit index is launched.[8] When a constituent fails to maintain a given credit rating or fails to sustain sufficient liquidity in the market, the constituent name is then replaced by the most liquid name in the market, with the condition that it satisfies the credit rating requirement. Although the previous series continues trading, liquidity is typically concentrated on the most recently updated series.

2.3.2 Credit Indices: Replication

Besides selling a CDS index protection, investors can obtain sector-wide credit exposure via selling a basket of single-name CDSs that replicates the cash flow of the CDS index. Denote $c_{idx,t}$ as the insurance cost of acquiring the index protection at time t, and $c_{bsk,t}$ as the cost of insurance on the same underlying entities via using a basket of single-name CDSs on the index constituents. We define the difference between $c_{bsk,t}$ and $c_{idx,t}$ as the basket-index spread (equation 2.1). According to the arbitrage pricing theorem, in a perfect capital market, index arbitraging activities would keep the basket-index spread close to zero (e.g., Junge and Trolle, 2015; O'Kane, 2011b; Couderc, 2007).

$$s_t = c_{bsk,t} - c_{idx,t} \tag{2.1}$$

Reconsider the iTraxx SovX WE CDS index example, with index fixed coupon $c_{idx} = 100$bps, notional amount of $A = 10,000,000\ USD$ and $M = 15$ constituent names. The seller of index protection would involve an initial upfront payment that equalises the contract's present value as zero. Now consider that the investor would prefer to sell the index protection via a basket of single-name CDSs. To replicate the cash flow of the index contract, the investor must enter a single-name CDS contract

[7] 85.5 percent (exceeds the 75 percent threshold) of private holders of the Greek sovereign bond agreed on sovereign debt restructuring. This is clarified as a credit event by ISDA (Coudert and Gex, 2013).

[8] In March and September of each year.

on each of the M names of the index, with the five-year maturity, the fixed coupon that is as the same as c_{idx}, and the notional amount of $A/M = \frac{1}{15} \times 10,000,000 = 666,667\ USD$ prior to the beginning of the trading. To ensure the present values of the single-name CDSs as zero, the aggregate amount of all upfront charges for all the 15 single-name CDS transactions is required from the investor. In the event of no default among the underlying constituents, the seller of the index protection receives a quarterly payment of $\frac{d}{360} \times c_{idx} \times \frac{M_t}{M} \times A = \frac{90}{360} \times 0.0100 \times \frac{15}{15} \times 10,000,000 = 25,000\ USD$. The protection seller of the basket of single-name CDSs receives a quarterly premium payment of $\sum_{m=1}^{M_t} \frac{d}{360} \times c_{idx} \times \frac{A}{M} = \sum_{m=1}^{15} \frac{90}{360} \times 0.0100 \times \frac{10,000,000}{15} = 25,000\ USD$.[9] In the event of Greece's debt restructure on 9th March 2012, the protection seller, via the basket of single-name CDSs, is obligated to deliver $\frac{A}{M} \times (1 - R_m) = \frac{1}{15} \times 10,000,000 \times 0.535 = 356,667\ USD$, with the quarterly premium payments reduced to $\frac{1}{4} \times \frac{14}{15} \times 10,000,000 \times 0.0100 = 23,333\ USD$ for the coming coupon dates. Both amounts (i.e., the loss given default payment and the adjusted quarterly payment) coincide with the cash flow of the protection seller via the CDS index as we mentioned previously.

Such reasoning applies to any possible default event of the underlying constituents until the index's maturity. Therefore, the payoffs for the seller of index protection and the seller of protection via single-name CDSs are identical. The overall basket level, c_{bsk}, is now obtained as the fixed spread on the basket of single-name CDSs that makes the replicating portfolio have zero net present value. This is also known as the intrinsic theoretical value of the CDS index, under no-arbitrage pricing theorem. Furthermore, when the individual CDS curves are flat and identical, the basket level is the duration weighted average of levels of the individual single-name CDSs. That is, $c_{bsk} \simeq \frac{\sum_{m=1}^{M} c_m \times RPV01_m}{\sum_{m=1}^{M} RPV01_m}$, wherein $RPV01_m$ is the risky present value of a basis point (O'Kane, 2011a,b). The detail handling and empirical replicating strategy are outlined below.

2.3.3 The CDS Data

We use the daily CDS data provided by the Markit. This includes the CDS indices and single-name CDS on individual constituents. Three CDS indices are examined in this study, namely, the iTraxx Europe Senior Financial Sector CDS index (Fin), the iTraxx Europe Non Financial Sector CDS index (NonFin), and the iTraxx Sovereign Western Europe CDS index (SovX). In terms of the constituents' list, the iTraxx NonFin contains 100 reference names of Europe's non-financial firms, the iTraxx Fin includes 25 large banks and financial firms in Europe, and the iTraxx SovX contains 15 single-name sovereign CDSs. The sample period for iTraxx Fin and NonFin indices is from January 03, 2006 to April 08, 2014. Because the iTraxx SovX was issued in 2009, the sample period ranges from September 20, 2009 to April 08, 2014. For liquidity reasons, we focus on the CDS contracts with five-year maturity, and prioritise the on-the-run series of CDS indices. Whenever

[9] $\frac{d}{360}$ is accrual time factor based on $\frac{ACT}{360}$ day count convention. $\frac{M_t}{M} \times A$ is the adjusted index notional amount with respect of M_t names of index, in case any defaults should happen.

multiple versions of the on-the-run CDS indices trade simultaneously, we opt for the latest version.[10]

To calibrate the insurance cost of the replicating CDS basket performance, we match the constituent names for each series of a CDS index, by using the annex documents provided by Markit. The credit term structure of the index and the corresponding constituent names are collected. The credit term structure includes the credit levels for six-month, one-year, two-year, three-year, five-year and seven-year CDS maturities, which are used to calibrate the default intensity for each individual name. The discount rates used here are bootstrapped from the libor rate, with maturity from one-month to twelve-month, and the interest rate swap, with maturity from two-year to seven-year.[11] With the default intensity, we reprice the single-name CDS by using the index documentation clauses.[12] By doing so, the impacts caused by the differences in the recovery rates and coupon rates between the single-name CDSs and the indices are strapped out. Besides, we also match the following clauses between the single-name CDSs and the indices: the currency of underlying notional (Euro for the iTraxx Fin and NonFin, USD for the iTraxx SovX), the restructuring clause, and the seniority of the underlying debt.[13] The weighted average of the new prices of the constituents' single-name CDSs is used as the basket-implied price for the CDS index. Finally, we convert the index price to derive the basket-implied level.[14]

2.3.4 The Basket-Index Spread

Figure 2.1 depicts the time series of the level of the 5-Year Markit iTraxx Europe Senior Financial CDS index, the implied level based on a basket of constituents' single-name CDSs, as well as the extracted basket-index spread from September 2006 to April 2014. We observe a non-zero basket-index spread over the sample period. This starts with a positive basket-index spread during the U.S. financial crisis, but turns into a negative spread during the EU sovereign crisis period. It returns to a positive spread right after the announcement of ECB regarding the Outright Monetary Transaction (OMT) on 6th September 2012. We expect the positive basket-index spread of the EU financial sector during the U.S. financial crisis to be due to market liquidity risk and funding risk. The defaults of major U.S. financial institutions froze one-third of the U.S. lending mechanism, pushing

[10] For example, on 9 March 2012, following the announcement of the credit event associated with Hellenic Republic, Markit re-versioned the iTraxx SovX as iTraxx SovX Western Europe Series 6 Version 2. With the new version, the weight of Hellenic Republic was set to zero and the notional of the index was reduced by 1/15. The version 1 was replaced by the version 2 in the market since the 9 March 2012 until new series is released. For dates with no quotes on the latest version, the quotes on previous version with the highest number of quote contributors are used.

[11] We follow the Markit 'locked-in' libor rate convention that the zero rates are fixed using the previous day's rates.

[12] For example the CDS on Greece actually has a recovery rate of 25% while the iTraxx SovX's recovery rate is 40%. We calibrate the default intensity with 25% recovery rate and then reprice the CDS on Greece with the same recovery rate of index (40%).

[13] When there are multiple clauses exist, we choose the No Restructure (XR) for the iTraxx EU family and Full Restructure (CR) for the iTraxx SovX family.

[14] The construction of basket measure follows exactly the same steps listed in the Markit CDS model documents. The basket value is akin to the intrinsic theoretical value of a CDS index (O'Kane, 2011b; Junge and Trolle, 2015; Brigo and Mercurio, 2007).

up the funding costs in the repo and inter-bank markets. Since both the mortgage-backed securities and CDO products were purchased by corporate and institutional investors globally, European banks and financial firms started waves of de-leveraging and fire-sale to pay back obligations, which accelerated the liquidity risk in the derivative market. Therefore, the frozen credit market and high funding costs increased the trading costs of a Europe CDS index arbitrager substantially during the U.S. financial crisis. Under such circumstances, for a highly leveraged arbitrager, it would be more expensive to construct the basket to insure all names than to trade via an index. Because the basket position requires investors to post the upfront payments and collaterals for all individual firms, the replication cost of the basket increases when the funding cost and liquidity risk of the financial market are high, causing a positive basket-index spread.

When the European sovereign debt crisis exploded in late 2009, the basket-index spread of the financial sector decreased into the negative territory, indicating that the financial sector CDS index was relatively more expensive than its basket benchmark. We argue that such a negative spread captures the market-wide systemic risk. This is because the correlation among the underlying constitutions' bonds surged throughout the EU crisis, indicating higher aggregate risk, pushing up the market insurance value of the CDS index relative to its basket benchmark, and leading to a declining basket-index spread as we observed.

Table 2.1 reports the summary statistics of the insurance costs of CDS indices and CDS baskets, and basket-index spreads for the iTraxx European non-financial (columns 1 to 3), senior financial (columns 4 to 6) and sovereign (columns 7 to 9) CDS indices. The top panel is the summary statistics for the whole sample period from January 2006 to April 2014. The middle panel reports the statistics for the non-EU crisis period, from January 2006 to June 2011, and the bottom panel reports the statistics for the EU crisis period, from July 2011 to April 2014. The reference for the crisis cut-off points is the business cycle indicator from the Centre for Economic Policy Research Euro Area Business Cycle Dating Committee.[15] A decrease in the spread between the CDS basket cost and the index cost means that the CDS index becomes more expensive relative to the constitutions' CDSs.

Over the prior-crisis sample, the mean index (basket) insurance cost is 97.07 (85.07) basis points in the non-financial sector, 81.05 (84.18) basis points in the financial sector, and 136.40 (142.28) basis points in the sovereign sector. While there are across-the-board increases in both the index and basket insurance cost from the pre-crisis to the crisis periods, the increase is much more pronounced for the financial sector (2.3 (2.2) times increase of the financial sector index (basket), versus 1.37 (1.35) times increase of the sovereign sector index (basket) and 1.28 (1.33) times increase of the non-financial sector index (basket)). Regarding the basket-index spread, we observe that the mean spread decreases for the financial and sovereign sectors during the European sovereign crisis period.

[15]See: http://cepr.org/content/euro-area-business-cycle-dating-committee

It is 3.04 basis points in the financial sector prior to the crisis and drops to 1.04 basis points over the crisis sample, which is a decrease of 66 percent. The sovereign basket-index spread declines by 21 percent from 5.85 basis points to 4.61 basis points. The non-financial sector has an increasing average basket-index spread from -1.93 basis points prior to the crisis to 2.60 basis points during the crisis. The results indicate that the systemic risk mainly presents in the financial and sovereign sectors in Europe.

Across the entire sample, the sovereign sector tends to have the highest average insurance cost of 167.48 basis points of index, 172.69 basis points of basket and a wide basket-index spread of 5.11 basis points. This might be due to the short history of the iTraxx Western Europe SovX index, which was issued in 2009, right at the onset of the European sovereign crisis. The average levels of the CDS index, basket, and spread for the financial sectors are 116.06, 118.42 and 2.37 basis points respectively. The non-financial sector has a negative but lowest mean basket-index spread of -0.41 basis points.

To provide a foundation for interpreting the empirical facts in the following sections, we first demonstrate the theoretical relationship between correlation and basket-index spreads through a simple insurance pricing example. We then empirically examine our basket-index spreads against existing systemic risk measurements in the literature. When we have quantitatively established the relationship between our basket-index spreads and systemic risk, we investigate the impact of crisis interventions news.

2.4 The Impact of Correlation: A Demonstration

The theoretical model of CDS index price, which is used to derive the basket implied spread in this chapter, assumes the default probabilities of constituents are independent of each other. It fails to consider the default correlations among different entities. In the following, we explain the impact of increasing correlations among the constituents' default probabilities on the basket-index spread measure. In particular, in a frictionless financial market, when the economy is stable with no systemic risk, the theoretical difference between the basket-implied spread and index is zero. (In reality, high transaction costs and different trading conventions in the single-name CDS market cause a high replication cost of the basket, leading to a positive basket-index spread.) During a financial crisis, elevated systemic risk increases default correlations among financial firms and sovereigns. A risk-averse investor, who expects such increasing default correlations, is willing to pay more in order to acquire insurance against aggregate downside defaults. The market price of the CDS index reflects investors' expectations of the increasing default correlations and aggregate sector-wide risks. As a result, the CDS index price is relatively higher than its basket opponent. This leads to a negative basket-index spread during the crisis. The higher the systemic risk perceived by investors, the higher the market price valued to a CDS index, and the further into the negative our basket-index spread would be. In addition, the more risk-averse an investor is, the more weight is placed on extreme downside aggregate outcomes, hence the further into the negative our basket-index spread would be.

2.4.1 The Benchmark

Consider a simple financial system with two banks, A and B. Both issue bonds with face values of £50 and have default probabilities of p_A and p_B respectively. A bondholder who wishes to insure against bank A's (B's) default on its bond can purchase a CDS contract on bank A (B) with an insurance cost of c_A (c_B) basis points per pound insured. For simplicity, the recovery rate in case of bank A (B) defaults is zero, and the discount rate is set at one. On $t = 0$, the protection buyer (bondholder) pays the insurance cost c_A (c_B) to the protection seller. On $t = 1$, if the bank A (B) defaults, the CDS seller pays the bond notional, £50, to the CDS buyer; if there is no default, the CDS contract ends. According to no-arbitrage theory, the c_A (c_B) can be backed out as the following.

$$c_A \times 50 = (1 - p_A) \times 0 + p_A \times 50 \quad \rightarrow \quad c_A = p_A$$
$$c_B \times 50 = (1 - p_B) \times 0 + p_B \times 50 \quad \rightarrow \quad c_B = p_B$$

Therefore, an investor who holds a basket of CDS contracts on both bank A and B faces an insurance cost of $c_{bsk} = (p_A{*}50{+}p_B{*}50)/100 = 0.5{*}(p_A{+}p_B)$ basis points per pound insured. Assuming there is no correlation between the default probabilities of bank A and B, a CDS index with constituents as bank A and B has the following default scenarios:

$$\begin{cases} \text{neither A nor B defaults:} & (1 - p_A) \times (1 - p_B) \\ \text{only A defaults:} & p_A \times (1 - p_B) \\ \text{only B defaults:} & (1 - p_A) \times p_B \\ \text{both A and B default:} & p_A \times p_B \end{cases}$$

The expected loss and insurance cost of the CDS index are:

$$\begin{aligned} \text{EL} &= \mathbb{E}[(1 - p_A) \times (1 - p_B) \times 0 + p_A \times (1 - p_B) \times 50 + (1 - p_A) \times p_B \times 50 + p_A \times p_B \times 100] \\ &= \mathbb{E}(50p_A + 50p_B) \end{aligned}$$

$$c_{idx} = \frac{\mathbb{E}(50p_A + 50p_B)}{100} = 0.5 * \mathbb{E}(p_A + p_B) \qquad \rightarrow \qquad c_{bsk} = c_{idx}$$

Set $p_A = p_B = p$,[16] then we have

$$c_{bsk} = c_{idx} = p$$

2.4.2 Default Correlation

Move one step ahead in time and assume that neither bank A nor B defaults. With exactly the same aforementioned scenario, an investor demands insurances against the potential defaults on these banks. However, the investor considers bank B as a systemically important bank, and is worried that bank B's default would cause a default of bank A, but not vice versa. We term the new beliefs about the default probabilities of the bank A and B as p'_A and p'_B. The market price of the CDS index c'_{idx} is changed as below.

$$\begin{aligned}
p'_A &= E(p + a_1\mathbf{1}_b) = p + E(a_1 p'_B) = (1 + \tilde{a}_1)p; \qquad p'_B = p \\
c'_{idx} &= E(p * [\frac{2(1-p) - a_1 p(1 - p - a_1 p)}{2(1-p) - a_1 p}]) \\
&= p * [\frac{2(1-p) - \tilde{a}_1 p(1 - p - \tilde{a}_1)p}{2(1-p) - \tilde{a}_1 p}]
\end{aligned}$$

Where $\mathbf{1}_b$ is an indicator function that equals one when bank B defaults and zero otherwise. $\tilde{a}_1 = E(a_1) \in [-1, 1]$ stands for the market expectation on the correlation between bank A's and bank B's default probabilities.

However, the basket is the theoretical price of an index, which is modelled with existing default probabilities on bank A and B.[17] Therefore, the basket-implied value stays the same, $c_{bsk} = p$. The theoretical basket-index spread with default correlation is,

$$\begin{aligned}
c_{bsk} - c'_{idx} &= p - p * [\frac{2(1-p) - \tilde{a}_1 p(1 - p - \tilde{a}_1)p}{2(1-p) - \tilde{a}_1 p}] \\
&= p * [\frac{-\tilde{a}_1(1 + \tilde{a}_1)p^2}{(1 - (1 + \tilde{a}_1 p)) + (1 - p)}] \\
&= p * [\frac{-\tilde{a}_1(1 + \tilde{a}_1)p^2}{(1 - p'_A) + (1 - p'_B)}] \leq 0 \qquad \forall \tilde{a}_1 \in [0, 1] \qquad (2.2)
\end{aligned}$$

[16] If the all single names in the basket share the same notional, recovery rate, maturity and other contract clauses, the spread of the CDS basket is a weighted average of the CDS premium of each name inside the basket. The CDS basket value (i.e., the theoretical CDS index value) is the risk present value per basis point (RPV01) weighted average of the single-name CDS premium as $c_{bsk} = \frac{\sum_{m=1}^{M} RPV01_m \times c_m}{\sum_{m=1}^{M} RPV01_m}$

[17] According to Markit, the intrinsic value of a CDS index (the basket-implied value) is published every morning when the market opens. The value is priced using previous date's quotes on the single-name CDSs. Therefore, the investors' expectations on the market today will not be reflected in the basket spread since it is constructed using yesterday's information.

Elevated correlations among the default probabilities indicate potential joint default scenarios with high market systemic risk. Equation (2.2) suggests that during the financial crisis, investors' expectations of high correlations among the underlying assets increase the index price higher than its basket benchmark, leading to a negative basket-index spread. Furthermore, the higher the expected correlation ($\tilde{a}_1$ or $E(a_1)$) is, the more expensive the CDS index is, and the further into the negative a basket-index spread would be.

The above theoretical model illustrates the direct relationship between the basket-index spread and the systemic risk embedded in the financial (and sovereign) market. It is essential to establish empirical evidence to support such an argument.

2.5 Empirical Motivation: The Systemic Risk

This section investigates the relationship between the basket-index spreads and the systemic risks of the non-financial, financial and sovereign sectors. We explore different systemic risk measures which are widely used in the literature. We study the direct relationship between our spread variable and these measures. The statistical findings provide us with empirical motivation confirming that the basket-index spread is significantly linked to the market-wide systemic risk. We start with a brief description of the data used to construct various risk measures, as well as the control variables. Then we present our findings on various aggregate risk measures, including the autocorrelation coefficients, the principal component factors, the counterparty risk and the risk-neutral implied correlation.

2.5.1 The Explanatory Variables

Studies by Longstaff, Pan, Pedersen, and Singleton (2011); Ang and Longstaff (2013) and Acharya, Drechsler, and Schnabl (2014) suggest that various risk factors contribute to the emergence of systemic risk in the financial and sovereign sectors, such as conditions in the local equity market and corporate credit market, liquidity and funding risks, government term structure, and exchange risk. We aim to capture the impact of these factors on our basket-index spread measure. The following describes the data and variable construction.

To capture the equity risk, we use the daily return of the STOXX 50 Index over the 1-month Euro libor rate. It is also essential to consider the market volatility risk. We construct a volatility risk premium as the difference between the VDAX index and the realised 30-day volatility of the DAX index. To capture the exchange risk of the EU, we use the return on the Euro/JPY currency swap. The realised volatility of the spot Euro/JPY rate is also used for the robustness test. A term premium is the risk taken by investors who hold a longer-term bond. The difference between the 10-year Euro interest rate swap rate and the 1-month Euro libor rate is calculated as the term premium.

Furthermore, the trading convention of the CDS market is mark-to-market. This requires investors to post collaterals based on the market value of the asset. Therefore, the market funding risk is crucial for CDS trading. It is constructed as the difference between the 3-month Euro libor rate and the Euro OIS rate. All of the above measures are downloaded from Bloomberg. For the robustness purpose, an additional measure 'depth', provided by the Markit, is used to capture the CDS product liquidity condition. The depth measure captures the number of quote contributors whose quotes are used to calculate the composite spread. Furthermore, we consider the credit market conditions by calculating two corporate spreads. Namely, the investment grade spread is the changes in the difference between the iBoxx BBB corporate bond effective yield and the iBoxx AAA corporate bond effective yield; and the high yield spread is the daily changes in the Bank of America/Merrill Lynch EU high yield effective spread rate. Data series for corporate spreads are obtained from the Federal Reserve Bank of St. Louis.

2.5.2 The Autocorrelation

Among various systemic risks reviewed in the literature, we construct two systemic risk proxies, which are the autocorrelation coefficient and the principal component factors, and explore their relationships with our basket-index spread measures. Getmansky, Lo, and Makarov (2004) and Billio, Getmansky, Lo, and Pelizzon (2012) suggest that the autocorrelation coefficients of assets returns can be perceived as indicators of market friction conditions.[18] In the strong version of the market efficient hypothesis, asset returns must not be forecastable since both public and private information are incorporated into the asset prices. In reality, market frictions such as transaction costs, collateral funding costs, and regulatory capital restrictions contribute to potential serial correlations in asset returns. As illiquidity is the most common form of market friction, we use the autocorrelation coefficient as an indicator of market imperfection. The variable is constructed as follows. The first order autocorrelation of each constituent's CDS level is estimated based on the previous 180 days' CDS premium observations. This uses the rolling-window estimation strategy. The autocorrelation variable is the equally weighted average of the constituents' autocorrelation coefficients. Figure 2.2 displays the time series of the average autocorrelation coefficient and the basket-index spread of the financial sector. There is a consistent co-movement between the basket-index spread and the autocorrelation average over the sample period, from September 2006 to April 2014. Such co-movement became stronger during the U.S. financial crisis, as well as the later stage of the EU sovereign crisis. It indicates that liquidity risk is a potential cause for surging basket-index spread in the European credit market during the U.S. financial crisis.

[18] $\rho_k = Cov[R_t, R_{t-k}]/Var[R_t]$ is the $k-$th order autocorrelation of asset return R_t (Billio, Getmansky, Lo, and Pelizzon, 2012).

2.5.3 The Principal Component Analysis

Modern financial architecture also increases the inter-connection among different assets. Furthermore, similar risk exposures created by advanced computing algorithms cause potential convergence trading behaviours during the financial crisis. These facts intensify the co-movement among different assets, which contributes to the emergence of potential systemic risk. In order to capture the common variations across different firms, we perform the principal component analysis on the constituents' equity returns as suggested in Bongaerts, De Jong, and Driessen (2011); Jobst and Gray (2013); Rodríguez-Moreno and Peña (2013) and Billio, Getmansky, Lo, and Pelizzon (2012).[19] The time series of the first three principal components are extracted to perform a correlation analysis. The estimation of the principal components is based on the previous 180 days' equity returns of the constituents. The correlation analysis aims to study the correlation structure among our basket-index spread and various systemic risk factors suggested in the literature (e.g., Longstaff, Pan, Pedersen, and Singleton, 2011; Pan and Singleton, 2008). The factors used are the European volatility premium, and the European equity index return. Figure 2.3 displays the time series of the first principal component and the basket-index spread of the iTraxx financial sector. We observe that the first principal component move in an opposite direction to the spread measure during the EU financial crisis. The first principal component is the factor that explains the largest proportion of cross-sectional variations in the constituents' equity returns. Therefore, as the aggregate systemic risk is the primary risk factor during crises, it is expected to observe a negative relation between the first principal component and the basket-index spread. That is, jumps in the systemic risk increase the price of the CDS index, and decrease the basket-index spread level.

Table 2.2 reports the principal component analysis and the correlation study. The top, middle and bottom panels depict the results for the non-financial, financial and sovereign sectors respectively. The first column reports the proportions of variations that are explained by each principal component. The second column reports the cumulative proportions of variations explained. The right panel of Table 2.2 presents the correlation matrix among the three components and various risk factors: namely, the basket-index spread, the European volatility risk premium, and the European equity market return. The results suggest that the first principal component explains approximately 45 percent of the cross-sectional variations in the equity returns for the non-financial sector, 67 percent for the financial sector and 71 percent for the sovereign sector. Cumulatively, the first three principal components explain 54 percent of the equity return behaviours of the non-financial sector, 78 percent of the financial sector, and 82 percent of the sovereign sector. Moving to the correlation analysis, we observe negative and statistically significant correlations between the first principal component and the basket-index spread measure for the financial sector. The European equity index return illustrates consistent negative correlations with all three components. The results suggest that the basket-index measure is significantly linked to the first principal component and explains a relatively fair amount of variations in the cross-sectional equity returns.

[19] For the sovereign sector, the equity indices are the MSCI country equity indices for each country.

2.5.4 The Counterparty Risk

Counterparty risk is the risk that a CDS protection seller, such as an investment bank, fails to make the payment delivery to the protection buyer when the underlying entity defaults. Studies by Arora, Gandhi, and Longstaff (2012) and Brigo and Mercurio (2007) show that a CDS contract is less valuable (i.e., a lower premium) when it has a higher counterparty risk. Furthermore, counterparty risk surges during a financial crisis, when the default correlation between a CDS underlying name and the protection seller of this CDS rises. Therefore, we expect that the counterparty risk has a negative impact on the basket-index spread. This is because the CDS indices are cleared by the central clearing house, where the clearing house has no or very low counterparty risk, while not all single-name CDSs are cleared. Therefore, the basket of single-name CDSs is exposed more to the counterparty risk than the corresponding index. This means that the basket is relatively less valuable, and hence reduces the basket-index spread. We expect that the higher the counterparty risk presents in the market, the lower the basket-index spread will be.

However, due to the opaque nature of the over-the-counter market, it is impossible to know the exact nature of counterparties without any private information as in Arora, Gandhi, and Longstaff (2012). To construct a counterparty risk measure, we follow the method outlined in Bai and Collin-Dufresne (2013) and Schweikhard and Tsesmelidakis (2012). Firstly, we collect the CDS prices for the list of primary dealers of the European Securities and Market Authorities (ESMA), who are certified by the European Primary Dealers Association (EPDA).[20] The list comprises the 27 largest international and regional banks such as Goldman Sachs, JP Morgan, Deutsche Bank, HSBC and ING.[21] It is not surprising that some of the dealers are also the main constituents of the iTraxx Fin CDS index. Secondly, a counterparty index is constructed as an equally weighted average of CDS premiums on every primary dealer, $CDS_{cp} = \sum_{k=1}^{K} \frac{1}{K} CDS_k$.[22] The third step is to calculate the beta coefficient between the changes in the CDS premium of the index's constituent entity m (i.e., ΔCDS_m) and the changes in the primary dealer CDS index (i.e., ΔCDS_{cp}), as shown in equation (2.3).

$$\beta_{cp}^{m} = \frac{Cov(\Delta CDS_m, \Delta CDS_{cp})}{Var(\Delta CDS_{cp})} \tag{2.3}$$

As the last step, a sector counterparty $\beta_{cp}^{i} = \sum_{m=1}^{M} \frac{1}{M} \beta_{cp}^{m}$ is calculated as the weighted average of the constituents' exposures to the counterparty risk for each sector i. The β_{cp}^{i} is used as an explanatory variable to study the impact of counterparty risk on the spread measure. A larger β_{cp} implies a higher likelihood of a joint default between the underlying entity of a CDS contract and the primary dealers, leading to less valuable single-name CDS protection.

[20] See: $https://www.esma.europa.eu/sites/default/files/library/list\_of\_market\_makers\_and\_primary\_dealers.pdf$

[21] The ESMA does update the dealer list at a timely fashion. All names listed from 2006 to 2014 are used to construct the index.

[22] The results do not change if the market capitalisation of each name is used to calculate the weight.

2.5.5 The Implied Correlation

The critical importance of correlation risk on portfolio asset pricing has been widely studied in the literature (e.g., Duffie, Eckner, Horel, and Saita, 2009; Kelly, Lustig, and Van Nieuwerburgh, 2016; Kelly, Pástor, and Veronesi, 2016; Tarashev and Zhu, 2008). Furthermore, default correlations among different assets could lead to a joint-default scenario, creating contagious and severe damages in an economy. Asset prices co-move together in dire economic conditions, particularly when the systemic risk is high. As suggested by Kelly, Lustig, and Van Nieuwerburgh (2016), realised correlations are backward-looking and potentially biased with noise. Therefore, we calculate a risk-neutral correlation implied from the CDS index, which helps to precisely measure the systemic risk of a market. The calculation of the implied correlation is based on the CDO tranche pricing literature. A CDS index is treated as a CDO tranche product with an attachment point of 0 and a detachment point of 100 percent.

To extract the implied correlations from the CDS indices, we assume the defaults of constituents follow an N-dimensional multivariate normal distribution governed by a one-factor Gaussian copula model. In particular, we assume that all constituents are homogeneous in sharing the same correlation. The default intensity of a single CDS on constituent m at time t is $\lambda_{m,t} = \sqrt{\rho} \times F_t + \sqrt{1-\rho} \times Z_{m,t}$, where F_t is a normally distributed random variable, and the $Z_{m,t}$ are mutually uncorrelated Gaussian random variables that govern the behaviours of idiosyncratic firm risks. $\lambda_{m,t}$ is constructed via simulation. Meanwhile, we bootstrap the $\tilde{\lambda}_{m,t}$ of firm m based on the single-name CDS premium observation from the market at time t. At each simulation point, we compare $\lambda_{m,t}$ against the $\tilde{\lambda}_{m,t}$. A default is assumed to happen if the simulated $\lambda_{m,t}$ exceeds the market-implied $\tilde{\lambda}_{m,t}$. We then find the optimal correlation that minimises the squared differences between the simulation-based CDS index premium versus the observed CDS index level ($\rho^* : \ \min(s^{sim}_{idx}(\lambda_{m,t}, \rho) - s_{idx})^2$).[23]

Figure 2.4 plots the time series of the risk-neutral default correlation implied by the iTraxx Fin CDS index from September 2006 to April 2014. The risk-neutral correlation is forward-looking and reflects market expectation of potential joint default event. We observe modest jumps in the correlation during the U.S. financial crisis, but a massive spike in the beginning of the EU sovereign crisis. It suggests that a high level of systemic risk was perceived by the market in financial sector. The time series for the non-financial and sovereign sectors are plotted in the appendix Figure A.1 and Figure A.2. We observe a similar behaviour pattern of the risk-neutral correlations in these two sectors during the crisis.

[23] The results remain the same when different default threshold criteria are used, such as the default intensity level of the CDS index.

2.5.6 The Regression Investigation

With the constructed counterparty risk and implied correlation measures, we now move to an empirical investigation to quantitatively assess the basket-index spread as a systemic risk measure. For each sector, we regress the return of CDS basket-index spread directly on the risk-neutral correlation. In a second setting, we include the counterparty risk exposed by each sector. Thirdly, additional explanatory variables that would contribute to explaining the non-zero basket-index spread are added as regressors in the model. Regarding the empirical framework, we opt for the Stock-Watson dynamic OLS proposed by Stock and Watson (1993). Such dynamic OLS estimators correct for possible simultaneity bias among the regressors. In systems where the variables autocorrelated of different orders but still co-integrate with each other, the simultaneity bias among the regressors can be dealt with via including the lagged and led values of the changes in the regressors. Table 2.3 reports the coefficient statistics from the dynamic OLS regression of basket-index spread returns on the implied correlations, which are extracted from CDS indices. The sample period focuses on the European sovereign crisis, from July 2011 to April 2014. In particular, one forward difference and one lagged difference of the implied correlation are included in the regressions. The Newey-West regression technique is used to control for series correlation and heteroskedasticity in the error terms.

The first three columns of Table 2.3 summarise the dynamic OLS regression results for the iTraxx European non-financial, financial and sovereign sectors respectively. Columns 4 to 6 are equivalent dynamic OLS regression results when controlling for market funding risk and counterparty risk. The results reported in columns 7 to 9 further control for the European equity index return, investment grade spread, high yield spread, term premium, volatility premium, and foreign exchange return. The regression findings suggest that the CDS basket-index spread measures are significantly explained by the implied correlations extracted from the CDS indices. The negative signs are confirmed with the theoretical model illustrated in section 2.4. This implies that higher correlations among the underlying assets lead to the relative price appreciation of the crash insurance product (i.e., the CDS index), which drive down the CDS basket-index spread measure. The scale of the coefficient on the implied correlation indicates that the financial sector is most sensitive to increases in the implied correlation, with a coefficient as large as -19.022. For a one point increase in the implied correlation, the sovereign sector reacts with a modest coefficient of -13.759, while the non-financial sector reacts with a coefficient of -9.665.

2.6 Government Bailout Action

The preliminary empirical investigation on the CDS basket-index spreads shows that the spread is strongly linked to four aggregate systemic risk measures in the literature. These findings motivate us to continue exploring the explanatory power of the basket-index spread. In this section, we study the impact of government bailout actions on the basket-index spread measure.

The past financial crisis witnessed a series of government interventions in the financial (and sovereign bonds) market to avoid an extreme catastrophic market-wide crash. Studies by Billio, Getmansky, Lo, and Pelizzon (2012); Kelly, Pástor, and Veronesi (2016) and Acharya, Drechsler, and Schnabl (2014) show that government bailout actions shift systemic risk from the financial sector to the sovereign sector. The work by Kelly, Lustig, and Van Nieuwerburgh (2016) suggests that investors expect the government to intervene in dire economic situations. The authors claim that such expectations of the implicit and explicit government guarantees and protection interventions contribute to explaining the underpricing of financial crash insurance products, in comparison to their theoretical benchmarks. Therefore, if the basket-index spreads indeed capture sector-wide systemic risk, they should react to government bailout actions. In particular, if a government news announcement is positive regarding bailout actions to stabilise the financial (or the sovereign) sector, the market expects that the systemic risk will be shifted away. Therefore, the prices of CDS indices would depreciate, leading to increasing basket-index spreads. On the other hand, a negative news announcement, which signals the reluctance of the government to bail out the financial (or the sovereign) sector, intensifies the market demands for crash insurance products. Hence, the prices of CDS indices appreciate and the basket-index spreads decrease.

This section proceeds as follows. We start with describing the data collection process of the government news events. This is followed by a brief elaboration on the news sentiment score construction. Afterwards, we visualise the basket-index spread movements around the event dates. The empirical findings on the government bailout actions are then presented and discussed.

2.6.1 The News Variable

To capture the government bailout action, we collect news articles and public statements on bailout actions issued by the central government and international organisations. The news articles are collected from two public resources: the International Monetary Fund (IMF) and the European Central Bank (ECB).[24] The news from IMF is identified by county of origin. The news from ECB is grouped by categories, such as banking, cooperation, monetary policy and stability. All these news articles are publicly available on the organisation's website. We exclude news that is merely a meeting transcript release.

With the collected news articles, we perform textual analysis on the news contents. We analyse the text of each news release in order to determine its sentiment direction. The analysis is used to determine whether a statement is positive towards government bailout action, which would help to stabilise the market and reduce systemic risk, or whether it is negative, which would reject potential bailout action in the private sector. The algorithm is the 'bag-of-words' sentiment analysis pro-

[24] We also collected the data from the European Commission (EC) for robust checks, the main results stay consistent.

gramme. It is an ordinary score-based algorithm that evaluates a piece of news based on the number of positive and negative words inside the article. A corresponding sentiment score is generated based on the textural analysis algorithm. A higher positive score indicates a higher probability of affirmative bailout actions by the corresponding authorities, while a lower negative score indicates worse outcomes regarding government interventions, such as a failure to achieve the agreement on a rescue plan. For the positive and negative words dictionary, we use the Loughran and McDonald sentiment word list from the Loughran and McDonald (2011).[25] Nevertheless, this dictionary is limited to the 10-K SEC filing documents from U.S. corporations. It may not be sufficient to perform content analysis on government actions. Therefore, we extend the dictionary with the MPQA Lexicons, including the opinion- and emotional-based Subjectivity Sense Annotations Lexicon, the Political Debate Corpus and the GoodFor/BadFor Corpus.[26] We construct two news variables from IMF and ECB.[27]

Figure 2.5 plots the event study on the basket-index spread of the financial sector. The event date zero is the day when a piece of government news on bailout action is announced to the public. The event window is three days post and prior to the news announcement. The top panel plots the average basket-index spread behaviour across all positive news, while the lower panel plots the spread behaviour across all negative news. The basket-index spread starts to increase two days prior to a positive news announcement, and continues to rise afterwards. On the other hand, a decreasing basket-index spread is observed one day prior to a negative news event day, and it continues to drop three days after the news is announced. Such behaviour aligns with our theory that positive (negative) news could cause the prices of CDS indices to depreciate (appreciate), which results in increasing (decreasing) basket-index spreads. The plots for the non-financial and the sovereign sectors are shown in the appendix: Figure A.3 and Figure A.4. Next, we perform regression analysis to investigate the impact of government bailout news on the systemic risk spread measure, controlling for various fundamental, technical and economic factors that might contribute to the persistent non-zero basket-index spreads.

2.6.2 Regression Analysis: The Bailout News

The empirical framework which is used here is the time series regression with Newey-West standard errors. It controls for the series correlation and heteroskedasticity in the error term. The regression is shown in equation (2.4) for public news statements from the ECB; and in equation (2.5) for news from the IMF. The dependent variable is the returns of basket-index spreads for iTraxx NonFin, Fin and SovX. The return is defined as $spread = \frac{basket-index}{index}$. The choices of explanatory variables (i.e., Xs) are based on Longstaff, Pan, Pedersen, and Singleton (2011); Ang and Longstaff (2013); Junge

[25] The list is downloaded from http://www3.nd.edu/ mcdonald/Word_Lists.html

[26] MPQA resource is sponsored by the University of Pittsburgh on annotated corpus, subjectivity lexicon and political debate data: http://mpqa.cs.pitt.edu/.

[27] News score on the European Commission is also constructed.

and Trolle (2015) and Pan and Singleton (2008). We include the European stock market excess return, high yield spread, investment grade spread, volatility risk premium, term premium, liquidity risk and exchange rate return. For robustness, the counterparty risk variable is also included in the regression. Furthermore, it is necessary to consider potential timing effect of the CDS market in reacting to government news. Besides performing the equation (2.4) and (2.5) on spontaneous news announcements, we also conduct the same regression on the lagged days after the news announcements, separately. We report the corresponding coefficients of γ for lagged day $k = 1, 2, 3$. The reported coefficients β_i^x of each control variable X are based on the regression on spontaneous news $News\ ECB_t$ and $News\ IMF_t$. The coefficients of control variables stay rather consistent when we regress the spreads on different lags of news. The sample period covers from January 2006 to April 2014 for the non-financial and financial sectors, and from September 2009 to April 2014 for the sovereign sector.

$$spread_{i,t} = \alpha_i + \beta_i^x X_{i,t} + \gamma_i New\ ECB_{t-k} + \epsilon_{i,t} \tag{2.4}$$

$$spread_{i,t} = \alpha_i + \beta_i^x X_{i,t} + \gamma_i New\ IMF_{t-k} + \epsilon_{i,t} \tag{2.5}$$

$$\forall k = 0, .., 3 \qquad i = \text{NonFin},\ \text{Fin},\ \text{SovX}$$

Table 2.4 reports the regression coefficients of basket-index spreads on news variables and various economic and financial factors. Panel A reports the regression statistics of equation (2.4) with ECB news announcements. The results of equation (2.5) with IMF news are reported in the bottom Panel B. In terms of bailout news variables, we observe a very interesting pattern. News announcements released by the ECB consistently have a significant impact on the basket-index spreads of the financial and sovereign sectors, while the news released by IMF only has a significant impact on the non-financial sector. The positive signs of the coefficients are expected. A positive news announcement increases the basket-index spread as it helps to stabilise the price of the crash insurance product. Economically, one standard deviation increase in the ECB news score induces a drop of 12.3 basis points in the insurance cost of the financial sector index, with respect to the theoretical price implied by the corresponding basket; and a relative drop of 17.3 basis points in the sovereign sector. One standard deviation increase in the IMF news score helps to stabilise the index insurance cost of the non-financial sector by 19.1 basis points in comparison to the implied basket cost. In addition, the impacts of news scores on the corresponding sectors are rather persistent. The 1-, 2- and 3-day lagged date variables post the news announcements consistently influence the basket-index spreads.[28]

The findings in Table 2.4 also suggest that the European excess equity return, changes in the investment grade spread and the counterparty risk illustrate consistent explanatory power for the non-zero basket-index spreads, across all three sectors. A higher equity return indicates the stock market is recovering from recession. Therefore, the insurance cost of a CDS index declines and the

[28]The significances and scales of the news score diminish after five days.

basket-index spread recovers. Consider the equation (2.4) for ECB news, one percent increase in the equity market excess return causes a relative drop in the index insurance cost by 45 basis points in the financial sector, by 76 basis points in the non-financial sector, and by 51 basis points for the sovereign sector. The changes in the investment grade spreads have uniformly positive signs on the spread returns across all three sectors. All underlying entities of the single-name CDSs in the basket are bonds of investment grade. As suggested by Arora, Gandhi, and Longstaff (2012); Augustin and Tédongap (2016), higher investment grade spread suggests stressed market conditions in the corporate investment grade bond market. For example, an outflow of capital from the corporate credit market increases the replication costs associated with the CDS basket trading, leading to a wider difference between the CDS basket and the index. In addition, the consistent significance of the counterparty risk variable suggests that it is crucial to monitor the credit default risks of primary dealers during the financial crisis. As indices are cleared in the central clearing house, but not all the single-name CDSs, a higher counterparty risk from these primary dealers reduces the insurance value of the CDS basket, generating a decreasing basket-index spread. Furthermore, for high yield spread, term premium and volatility premium, we observe modest explanatory powers. Regarding the high yield spread, which is considered as an important risk factor in the study of Longstaff, Pan, Pedersen, and Singleton (2011), an increase in the high yield spread may suggest deterioration in the corporate credit market. This is a signal for potential financial crisis. As a result, the prices of CDS indices increase and the basket-index spreads decrease. This is why an increase in the corporate high yield spread has a negative impact on our systemic risk measure. The adjusted R-squared of equation (2.4) (the ECB news announcements) for the non-financial, financial and sovereign sectors are 18.9 percent, 16.6 percent, and 14.8 percent respectively.

2.7 Robustness Regressions

This section discusses various robustness regressions that we conduct on the basket-index spread measures. It includes the tests on the market liquidity risk and the arbitrage trading returns. In addition, the forecastability of our systemic risk measure is also explored via in-sample and out-of-sample regression analyses. At the end, we present an asset pricing model with the systemic risk by using the Fama-MacBeth cross-sectional regression.

2.7.1 Liquidity Risk and Arbitrage Returns

The study conducted by Junge and Trolle (2015) adopts a similar fashion measure. The authors use the absolute value of the CDS basket-index spread as a measure of liquidity risk. For robustness purposes, we test the basket-index spreads directly on the market liquidity condition of the CDS indices. Markit provides information on the 'depth' of the CDS index market. It is the number of contributors who quote to trade the CDS index. If our basket-index spread is a liquidity measure, instead of the systemic risk, we shall observe a positive coefficient on the 'depth', since a higher value of 'depth' implies greater liquid market condition, lower transaction costs with CDS indices, and hence wider basket-index spreads. We name the market 'depth' the market liquidity risk and include it in the regression equations (2.4) and (2.5). The results are presented in Table 2.5. Interestingly, the findings suggest a negative impact of the CDS index's 'depth' on the spreads. Actually, the explanation favours a systemic risk story. During a financial crisis, more investors demand crash insurance products such as the CDS indices. The increasing demand pushes up the prices of CDS indices, and negatively impacts the spreads. The results on the equity excess return, counterparty risk, and the bailout news scores, stay robust.

The persistent non-zero spread between the insurance costs of a CDS basket versus a CDS index also provides excellent arbitrage opportunities. The intrinsic value of a CDS basket is constructed conditional on the no-arbitrage theory. Therefore, we test whether the non-zero basket-index spreads that are observed in Figure 2.1 is the returns of a CDS index arbitrager. If this is the case, when an arbitrage return variable is included in the regression equations (2.4) and (2.5), we would expect the bailout news scores to be no longer significant to explain the basket-index spreads, nor these macroeconomic variables. We construct an arbitrage return variable with the following trading strategy. Assume in a financial market with no ex-ante information leakage and no transaction cost, a CDS arbitrager can only engage in trading activity on the event day when a piece of government news is released to the public. If it is positive news, the arbitrager immediately sells CDS index protection at the current premium and buys the protections on the basket. When the CDS index price drops after the positive news, the investor earns the difference. The arbitrager keeps the current position if there is no negative news. When a government announcement is perceived as negative, the arbitrager switches the trading strategy: buying the protection on the index and selling the protection on the basket.[29] The regression results from including the arbitrage returns are reported in Table 2.6. We do not observe any significance of the arbitrage returns in explaining the variations in the basket-index spreads for the non-financial and sovereign sectors, while it does explain the variations for the financial sector. Most importantly, the finding on the government bailout news remains robust. The ECB news scores continue to significantly impact the systemic risks in the financial and sovereign sectors, as does the IMF's news on the non-financial sector. The explanatory powers of the equity excess market return and the counterparty risk stay unaltered. Therefore, we conclude that the arbitrage activity cannot fully explain the persistent non-zero basket-index spreads.

2.7.2 Forecastability: Risk Reversal

We have established the fact that the CDS basket-index spread measure can capture the systemic risks embedded in different sectors. A logical following step is to test its predictability. This section investigates whether the proposed systemic risk measure can predict the volatility movement in the

[29] Assume there is no addition liquidation cost on existing positions.

option market. We focus on the risk reversal (RR), which is constructed with the OTM put options on the stock index. The OMT index put option has widely been used in the literature to study the systemic risk (e.g., Kelly, Lustig, and Van Nieuwerburgh, 2016; Kelly, Pástor, and Veronesi, 2016; Driessen, Maenhout, and Vilkov, 2009). Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015) suggest that the risk reversal captures the disaster risk in the equity market since a put option on the stock index insures against a sector-wide price drop.[30] The risk reversal is the trading return when a trader buys an OTM call and sells an OTM put with the same maturity and symmetric moneyness. We define the risk reversal as in equation (2.6): the premium difference between an OTM call option and an OTM put option, which have the same underlying asset (i), maturity (T) and moneyness (Δ), over the premium of the OMT call option.

$$RR = \frac{C_{i,T,\Delta} - P_{i,T,\Delta}}{C_{i,T,\Delta}} \tag{2.6}$$

In particular, we use the options on the STOXX 50 stock index, with 1 month maturity and a moneyness of 25.[31] During the crisis period, the price of the OTM put option is more expensive relative to the corresponding OTM call option. Therefore, the risk reversal measure decreases, even into negative. Such a behaviour pattern is akin to the movement of the basket-index spread illustrated in Figure 2.1. Therefore, we expect a positive coefficient. The regression framework continues as time series regression with Newey-West standard errors for equation (2.7). This explores the predicting power of the spread measure in forecasting future systemic risk movement implied by the option market. An interaction term between the basket-index spreads and the news scores is included, in order to test the effectiveness of governments' intervention policies. If a government bailout action actively reduces the systemic risk, the coefficient on the spreads is depressed downward. The marginal impact of the bailout news yields a negative coefficient of the interaction term.

$$\begin{aligned} RR_t =& \alpha_i + \beta RR_{t-1} + \gamma_i spread_{i,t-1} + \phi^n News^n_{t-1} + \eta^n_i spred_{i,t-1} News^n_{t-1} + \epsilon_t \\ i =& \text{NonFin}, \ \ \text{Fin}, \ \ \text{SovX} \qquad n = \text{ECB, IMF} \end{aligned} \tag{2.7}$$

Table 2.7 depicts the regression results. The regression results suggest that the lagged spreads positively predict the option risk reversals. The coefficients are significant at 1 percentage level for all three sectors. Furthermore, negative coefficients are observed on the lagged interaction term. This suggests that bailout policy interventions indeed help to improve market stability and lower the expected systemic risk. The significance of the interaction term is observed on the financial and sovereign sectors.[32] This is as expected since the crisis exploded in these two sectors. The adjusted R-squared for the non-financial and financial sectors are approximately 37 percent, and as high as 52 percent for the sovereign sector.

[30] See Kelly, Lustig, and Van Nieuwerburgh (2016); Kelly, Pástor, and Veronesi (2016).

[31] We vary the moneyness from 10 to 30, the results remain consistent.

[32] We also test the results by including both ECB and IMF news in the same regression. The ECB news impact dominates the IMF news on the financial sector. But IMF news remains significant for the sovereign sector.

Next, we perform the out-of-sample predication to statistically test the predicting power of our spread systemic risk measure. We compare the model (equation 2.10) against two benchmarks, a simple random walk (equation 2.8) and a AR(1) process (equation 2.9) of the risk reversal. The Clark and West F-test is performed on the null hypothesis that our model does not outperform the benchmarks in the out-of-sample period. We perform the rolling windows forecasting with a window size of 180 days.

$$E_t(RR_{t+1}) = \hat{\alpha}_i \tag{2.8}$$

$$E_t(RR_{t+1}) = \hat{\alpha}_i + \hat{\beta} RR_t \tag{2.9}$$

$$E_t(RR_{t+1}) = \hat{\alpha}_i + \hat{\beta} RR_t + \hat{\gamma}_i spread_{i,t} \tag{2.10}$$

$$i = \text{NonFin}, \;\; \text{Fin}, \;\; \text{SovX}$$

The out-of-sample test results are reported in Table 2.8. The first row reports the estimated coefficient $\hat{\gamma}$ of the basket-index spread in equation (2.10). The estimated coefficients have considerably large economic scales, especially as high as 2.989 of the sovereign sector's spread. In the lower panel, the first two rows report the Clark and West F-test statistics of our model against the random walk model, and the corresponding t-statistics. The last two rows report the F-test and t-statistics when comparing our model against the AR(1) process. When comparing against the random walk, the t-statistic is 4.91 for the non-financial sector, 4.84 for the financial sector and 5.16 for the sovereign sector, at 1 percentage significance level. For the AR(1) process, the t-statistics are 3.36, 2.01 and 2.61 for the non-financial, financial and sovereign sectors respectively. Therefore, we can reject the null in both benchmark cases and conclude that the basket-index spreads have superior predicting powers on the movement of option risk reversal than both benchmarks.

2.7.3 Asset Pricing: Fama-MacBeth Regression

As a final check, we perform an asset pricing test via the Fama-MacBeth cross-sectional regression. If systemic risk is a risk factor that is priced by the market, we expect the CDS basket-index spread to explain the cross-sectional variations of stock returns. The data-set used in this investigation is the 25 European portfolios formed on size and book-to-market. It is downloaded from the data library generously provided by Kenneth R. French.[33] We adopt the standard Fama-French three factors asset pricing model, which are the equity market return, the firm size, and the high minus low factor. The CDS basket-index spreads are included as a fourth pricing factor. The regression results are reported in Table 2.9. The first four columns report the factor loading on each risk factor. The second four columns report the price of risk. The t-statistics are reported in the squared brackets. Focusing on our spread systemic risk measure, the factors' loadings of the financial and sovereign sectors (column 4) are statistically significant, as are the prices of the factors (column 8).

[33] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The last three columns report the adjusted R-squared, the Chi-square statistics and the HJ distance test. The null for the Chi-square test and the HJ distance test is that: there is a joint zero pricing error. In all cases, we fail to reject the null and conclude that there is a joint zero pricing error in our model. That is, the spread systemic risk measure proposed in this paper indeed has a sufficient pricing power in the cross-sectional portfolio returns.

2.8 Conclusion

In this paper, we propose a systemic risk measure named the basket-index spread. It is the price difference between a basket of single-name CDSs and a CDS index. We find that this spread measure is significantly related to four aggregate systemic risk measures studied in the literature. Furthermore, we find a negative relationship between the basket-index spread and the risk-neutral default correlation. A simple theoretical model is presented for demonstration. We also investigate the impact of bailout interventions from the ECB and the IMF on the sector-wide systemic risk during the crisis. We find common risk factors such as equity index excess returns, investment grade spread and counterparty risk significantly influence the systemic risk level cross-sectionally. Furthermore, alternative explanatory variables such as market liquidity risk and arbitrage trading returns fail to explain the persistent non-zero basket-index spread. On the other hand, we find that government bailout news significantly impacts on the sector-wide systemic spread measure. Furthermore, different sectors react to different news sources. The financial and sovereign sectors have strong reactions towards news released by the ECB, whereas the non-financial sector responds to the IMF news. Additional predictability tests on the systemic spread measure are performed.

Ongoing work involves building the theoretical motivations behind the basket-index measure. More comprehensive linguistic and textual analyses on government news are encouraged for news studies. It is also essential to provide supportive evidence that a positive basket-index spread is a measure of liquidity risk. In addition, it is worth extending the spread systemic risk measure by using U.S. CDS products.[34]

[34] Kallestrup, Lando, and Murgoci (2016); Kelly, Pástor, and Veronesi (2016); Billio, Getmansky, Lo, and Pelizzon (2012); Schweikhard and Tsesmelidakis (2012)

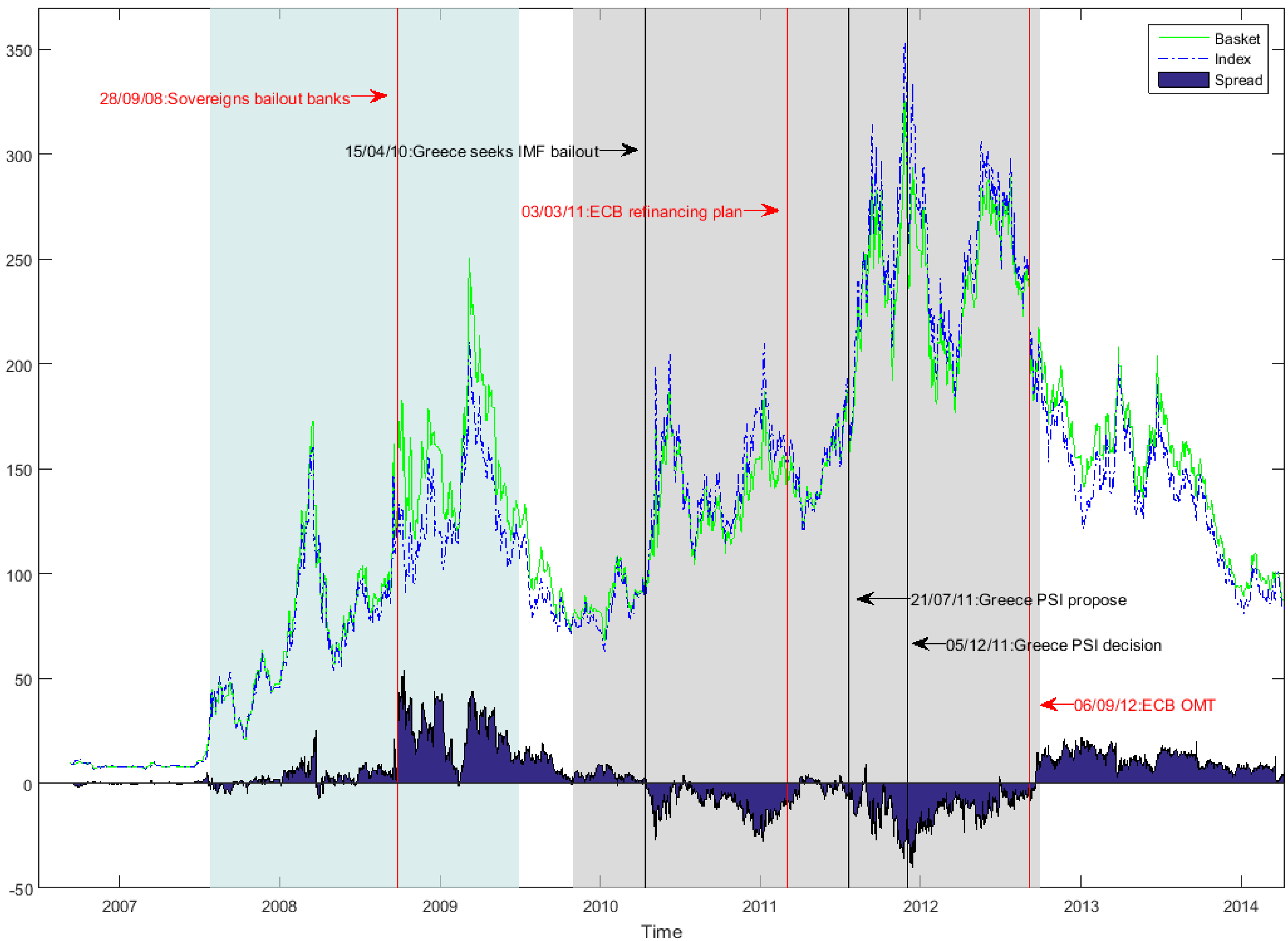


Figure 2.1. Time Series of CDS Basket, Index and Basket-Index Spread: Financial Sector

The figure plots the insurance cost of the European financial sector based on the basket of CDSs (dotted blue line) and the CDS index (solid green line), as well as the basket-index spread (blue shaded area) from September 2006 until April 2014. Units are basis points. Time to maturity is 5 years. The cyan vertical bar represents the U.S. financial crisis. The grey vertical bar represents the European sovereign crisis.

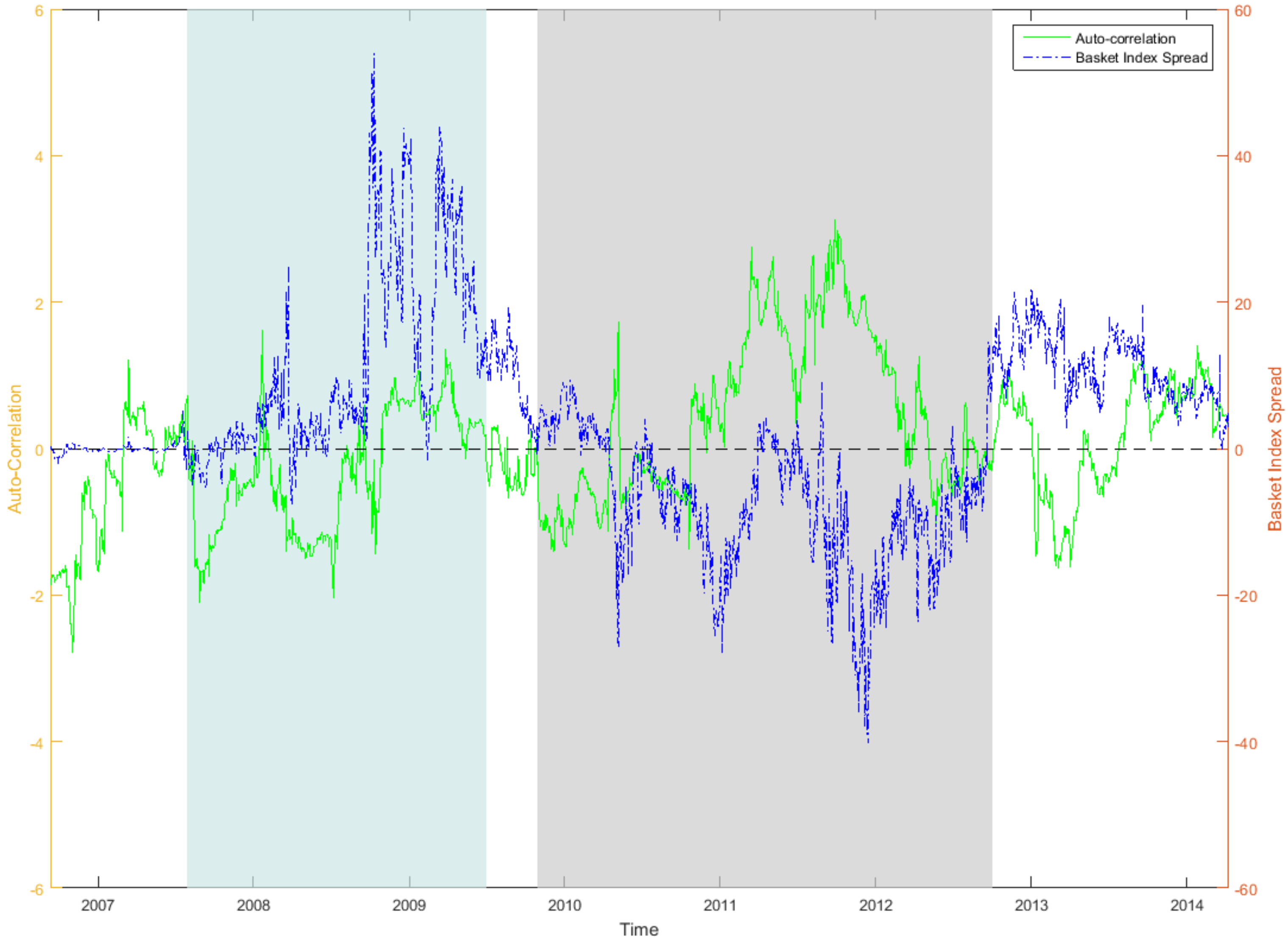


Figure 2.2. Autocorrelation vs. Basket-Index Spread: Financial Sector

The figure plots the 6-month rolling window equally-weight autocorrelation coefficient of the financial CDS constituents' equity returns (solid green line) and the basket-index spread (dotted blue line) from September 2006 until April 2014. The cyan vertical bar represents the U.S. financial crisis. The grey vertical bar represents the European sovereign crisis.

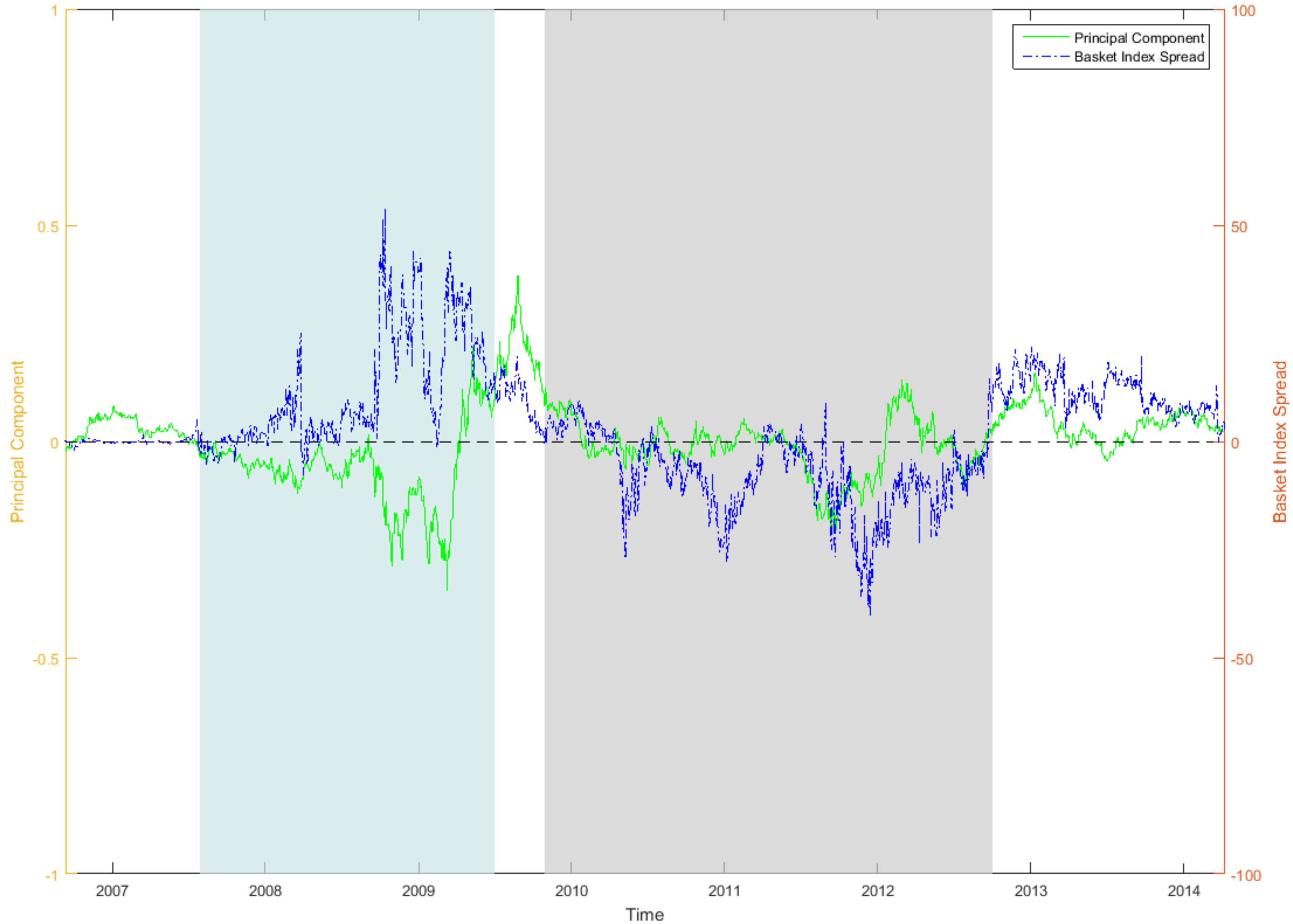
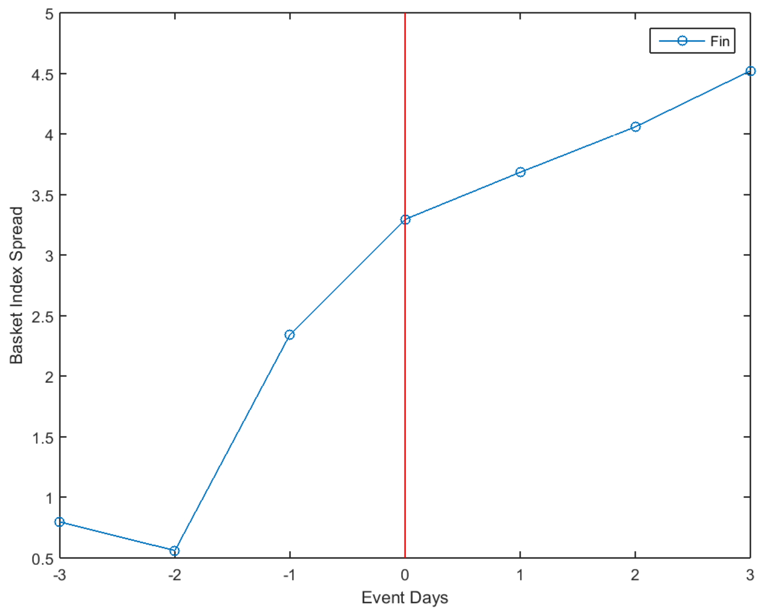


Figure 2.3. 1st Principal Component vs. Basket-Index Spread: Financial Sector

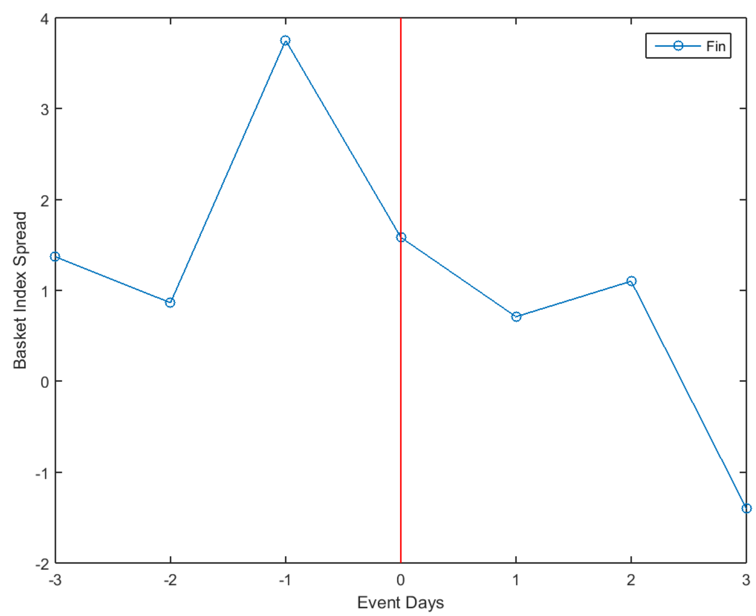
The figure plots the time series of the first principal component of the financial sector constituents' equity returns (solid green line) and the basket-index spread (dotted blue line) from September 2006 until April 2014. The cyan vertical bar represents the U.S. financial crisis. The grey vertical bar represents the European sovereign crisis.

Figure 2.4. Risk-Neutral Implied Default Correlation: Financial Sector

The figure plots the time series of the risk-neutral default correlation for the financial sector. The sample period is from September 2006 to April 2014. The cyan vertical bar represents the U.S. financial crisis. The grey vertical bar represents the European sovereign crisis.



(a) Positive News



(b) Negative News

Figure 2.5. Average Basket-Index Spread Across Event Days: Financial Sector

The figures plot the average financial basket-index spread of CDS financial sector outside a +/- 3-day interval around government news announcement. The top panel uses positive news and the lower panel uses negative news.

Table 2.1. Summary Statistics: Basket, Index and Basket-Index Spread

This table reports the summary statistics of daily levels of CDS indices, baskets of single-name CDSs and basket-index spreads for the European non-financial, financial and sovereign sectors. Units are in basis points. The statistics include mean, standard deviation (SD), median, minimum (Min), maximum (Max), skewness (Skew), kurtosis (Kurt) and observation number (N). Panel A is the full sample period from January 2006 to April 2014. Panel B is the pre-European sovereign crisis from January 2006 to June 2011. Panel C is the European sovereign crisis from July 2011 to April 2014. The reference of the business cycle indicator is from the Centre for Economic Policy Research Euro Area Business Cycle Dating Committee.

Panel A: Full Sample, January 2006 ~ April 2014

	NonFin			Fin			SovX		
	Index	Basket	Spread	Index	Basket	Spread	Index	Basket	Spread
Mean	95.18	94.72	-0.41	116.06	118.42	2.37	167.48	172.69	5.11
SD	46.92	46.18	6.72	77.30	75.07	13.25	95.56	94.39	7.75
Median	94.03	94.68	0.47	116.44	123.76	0.91	141.33	146.01	5.15
Min	24.17	23.17	-26.19	6.81	7.13	-36.51	41.96	47.95	-21.93
Max	324.52	279.64	11.01	353.00	325.68	41.93	385.66	384.75	31.24
Skew	0.76	0.67	-1.29	0.44	0.17	0.15	0.64	0.61	-0.17
Kurt	4.03	3.90	5.46	2.71	2.34	4.41	2.12	2.06	5.15
N	2156	2156	2156	2156	2156	2156	1096	1096	1096

Panel B: Pre-Europe Sovereign Crisis, January 2006 ~ June 2011

	NonFin			Fin			SovX		
	Index	Basket	Spread	Index	Basket	Spread	Index	Basket	Spread
Mean	87.07	85.07	-1.93	81.05	84.18	3.04	136.40	142.28	5.85
SD	51.79	50.70	6.92	56.03	58.40	12.33	51.05	53.21	6.14
Median	88.21	87.33	-0.84	83.33	88.98	0.32	146.82	151.37	5.27
Min	24.17	23.17	-26.19	6.81	7.13	-36.51	41.96	47.95	-10.46
Max	324.52	279.64	11.01	210.60	250.68	41.93	242.77	249.39	31.24
Skew	1.13	1.13	-1.27	0.08	0.07	0.98	-0.26	-0.27	0.47
Kurt	4.38	4.43	5.30	1.75	1.83	5.42	1.92	1.86	3.68
N	1435	1435	1435	1435	1435	1435	438	438	438

Panel C: European Sovereign Crisis, July 2011 ~ April 2014

	NonFin			Fin			SovX		
	Index	Basket	Spread	Index	Basket	Spread	Index	Basket	Spread
Mean	111.30	113.93	2.60	185.74	186.56	1.04	188.18	192.93	4.61
SD	29.25	26.64	5.10	65.78	55.59	14.83	111.42	109.27	8.62
Median	106.61	110.16	3.73	170.99	180.29	5.57	117.19	123.73	5.03
Min	63.80	69.83	-18.06	81.07	89.14	-36.51	43.37	52.02	-21.93
Max	190.29	186.42	11.01	353.00	325.68	30.21	385.66	384.75	31.24
Skew	0.40	0.35	-1.16	0.29	0.10	-0.71	0.26	0.26	-0.23
Kurt	2.28	2.24	4.47	2.01	2.14	2.73	1.36	1.34	4.84
N	721	721	721	721	721	721	658	658	658

Table 2.2. Principal Component Analysis

This table reports the summary statistics for the principal components analysis and the correlation analysis from January 2006 to April 2014 for the European non-financial, financial and sovereign sectors. The PCA analysis is reported on the left-hand side of the table based on the correlation matrix of daily equity returns for CDS indices' constituents. Columns 1 and 2 report the variation proportion explained by individual components respectively and cumulatively. The right-hand side of the table reports the correlation analysis between the first three principal components and three potential risk factors. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

Principal Component Analysis			**Correlation Analysis**		
		NonFin			
Component	**Proportion**	**Cumulative**	**Spread**	**Volatility**	**Equity Return**
First	0.4428	0.4428	0.1063*	0.0441	-0.0087
Second	0.0507	0.4935	-0.0313	0.0078	-0.1257*
Third	0.047	0.5405	0.0092	-0.0217	-0.0342
		Fin			
Component	**Proportion**	**Cumulative**	**Spread**	**Volatility**	**Equity Return**
First	0.6723	0.6723	-0.0693*	-0.1736*	-0.0145
Second	0.0559	0.7282	-0.0334	-0.0445	-0.018
Third	0.0501	0.7783	-0.0348	-0.0371	0.0634*
		SovX			
Component	**Proportion**	**Cumulative**	**Spread**	**Volatility**	**Equity Return**
First	0.7111	0.7111	-0.0177	0.0175	-0.2106*
Second	0.0609	0.772	0.0355	0.0692	0.0269
Third	0.0454	0.8174	0.0159	-0.011	-0.0279

Table 2.3. Dynamic OLS: Basket-Index Spread and Implied Correlation

This table reports the coefficient statistics of the dynamic OLS regressions of basket-index spread returns on the CDS index implied correlations. One forward and one lagged difference of the implied correlation are also included. The Newey-West standard error is used to correct serial correlation and heteroskedasticity. The first three columns summarise the regression results for the European non-financial, financial and sovereign sectors respectively. Columns 4 to 6 are equivalent dynamic OLS regression results when controlling for market funding risk and counterparty risk. The results reported in columns 7 to 9 further control for equity return, investment grade spread, high yield spread, term premium, volatility premium, foreign exchange return. The sample period is the European sovereign crisis from July 2011 to April 2014. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	NonFin	**Fin**	**SovX**	**NonFin**	**Fin**	**SovX**	**NonFin**	**Fin**	**SovX**
Implied Correlation	-9.894***	-19.774***	-14.174***	-9.491***	-19.087***	-13.605***	-9.665***	-19.022***	-13.759***
Market Funding Risk				-0.036	-0.042	-0.006	-0.017	-0.012	0.005
Counterparty Risk				-0.752***	-1.176***	-0.605***	-0.185**	-0.358***	-0.159
Equity Return							0.620***	1.311***	0.537***
Investment Grade							0.018***	0.038***	0.011
High Yield							-9.720***	-6.230**	-2.673
Term Premium							-0.006	-0.097**	0.054
Volatility Premium							0.001**	0.003***	-0.002***
FX Return							5.639	11.881	24.986
Constant	1.107***	2.173***	1.592***	1.062***	2.098***	1.530***	1.081***	2.090***	1.547***
N	721	721	658	721	721	658	721	721	658
R^2	0.370	0.532	0.401	0.484	0.632	0.433	0.585	0.728	0.474
Adjusted R^2	0.367	0.530	0.398	0.481	0.629	0.429	0.578	0.724	0.465

Table 2.4. Time Series Regression: Basket-Index Spread and Government News

The following table reports the time series regression with Newey-West standard errors for the basket-index spread returns of the European non-financial, financial and sovereign sectors. Explanatory variables include equity return, market funding risk, investment grade spread, high yield spread, term premium, volatility premium, foreign exchange return, counterparty risk and the news scores of government policy announcements. The sample period is from January 2006 to April 2014 for the non-financial and financial sector, and from September 2009 to April 2014 for the sovereign sector. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance. Panel A uses the news scores based on the ECB news, and panel B uses the news scores based on the IMF news. In order to avoid multi-collinearity, the regression includes only one news score sequence at a time. That is, four regressions are performed to obtain the coefficients of the contemporaneous, 1-, 2- and 3-day lagged news variables. The coefficients for other explanatory variables and the adjusted R-squared are based on the regressions with a contemporaneous news score.

Panel A: ECB News

	NonFin	**Fin**	**SovX**
Equity Return	0.450***	0.760***	0.510***
Market Funding Risk	0.002	0.000	0.003
Investment Grade	210.8***	205.8***	124.2***
High Yield	-8.887***	-4.081	-1.999
Term Premium	0.066*	0.151**	0.020
Volatility Premium	-0.000	-0.005***	-0.001*
FX Risk	18.27	13.77	57.16
Counterparty Risk	-0.182***	-0.260***	-0.150***
News ECB	-0.002	0.026***	0.025***
News ECB (Lag 1)	-0.006	0.021***	0.024***
News ECB (Lag 2)	-0.003	0.024***	0.018**
News ECB (Lag 3)	-0.002	0.027***	0.017**
Constant	-0.003	0.029***	0.048***
N	2,155	2,155	1,095
Adjusted R^2	0.125	0.163	0.107

Panel B: IMF News

	NonFin	**Fin**	**SovX**
Equity Return	0.445***	0.768***	0.544***
Market Funding Risk	0.002	-0.000	0.003
Investment Grade	207.2***	212.8***	144.7***
High Yield	-8.960***	-3.821	-1.455
Term Premium	0.063*	0.155**	0.009
Volatility Premium	-0.000	-0.005***	-0.001*
FX Risk	19.56	10.95	53.28
Counterparty Risk	-0.180***	-0.260***	-0.157***
News IMF	0.027***	-0.003	0.009
News IMF (Lag 1)	0.028***	-0.001	0.009
News IMF (Lag 2)	0.024***	-0.007	0.003
News IMF (Lag 3)	0.026***	-0.002	0.010
Constant	-0.005*	0.032***	0.049***
N	2,155	2,155	1,095
Adjusted R^2	0.134	0.155	0.096

Table 2.5. Robust Regression: Control for Liquidity Risk

The following table reports the time series regression with Newey-West standard errors for the basket-index spread returns of the European non-financial, financial and sovereign sectors. Explanatory variables include equity return, market funding risk, investment grade spread, high yield spread, term premium, volatility premium, foreign exchange return, counterparty risk and the news scores of government policy announcements. In addition, a market liquidity risk factor is included in the regression. The sample period is from January 2006 to April 2014 for the non-financial and financial sector, and from September 2009 to April 2014 for the sovereign sector. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance. Panel A uses the news scores based on the ECB news, and panel B uses the news scores based on the IMF news. In order to avoid multi-collinearity, the regression includes only one news score sequence at a time. That is, four regressions are performed to obtain the coefficients of the contemporaneous, 1-, 2- and 3-day lagged news variables. The coefficients for other explanatory variables and the adjusted R-squared are based on the regressions with a contemporaneous news score.

Panel A: ECB News

	NonFin	**Fin**	**SovX**
Equity Return	0.480***	0.759***	0.513***
Market Funding Risk	0.002	-0.000	0.003
Investment Grade	208.0	212.6	139.7
High Yield	-8.645***	-4.306	-1.193
Term Premium	0.064*	0.149**	0.025
Volatility Premium	0.000	-0.005***	-0.001*
FX Risk	20.92	12.30	50.22
Counterparty Risk	-0.175***	-0.262***	-0.151***
Market Liquidity Risk	-0.025***	-0.002*	-0.023***
News ECB	0.000	0.025***	0.022***
News ECB (Lag 1)	-0.003	0.020***	0.022***
News ECB (Lag 2)	-0.001	0.023***	0.015**
News ECB (Lag 3)	0.001	0.026***	0.015**
Constant	0.075***	0.043***	0.338***
N	2,155	2,155	1,095
Adjusted R^2	0.189	0.166	0.148

Panel B: IMF News

	NonFin	**Fin**	**SovX**
Equity Return	0.477***	0.766***	0.542***
Market Funding Risk	0.002	-0.001	0.003
Investment Grade	205.4	219.3	158.5
High Yield	-8.691***	-4.078	-0.689
Term Premium	0.062*	0.152**	0.015
Volatility Premium	0.000	-0.005***	-0.001*
FX Risk	21.81	9.64	46.61
Counterparty Risk	-0.173***	-0.262***	-0.158***
Market Liquidity Risk	-0.025***	-0.002*	-0.023***
News IMF	0.025***	0.001	0.009
News IMF (Lag 1)	0.026***	0.003	0.010
News IMF (Lag 2)	0.022***	-0.003	0.004
News IMF (Lag 3)	0.024***	0.002	0.011
Constant	0.073***	0.047***	0.348***
N	2,155	2,155	1,095
Adjusted R^2	0.196	0.159	0.140

Table 2.6. Robust Regression: Control for Trading Return

The following table reports the time series regression with Newey-West standard errors for the basket-index spread returns of the European non-financial, financial and sovereign sectors. Explanatory variables include equity return, market funding risk, investment grade spread, high yield spread, term premium, volatility premium, foreign exchange return, counterparty risk and the news scores of government policy announcements. Two additional control variables are included in the regression. A market liquidity risk factor measures the number of contributors for CDS indices. A trading return variable captures the expected returns of CDS index arbitrage activities. The sample period is from January 2006 to April 2014 for the non-financial and financial sector, and from September 2009 to April 2014 for the sovereign sector. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance. Panel A uses the news scores based on the ECB news, and panel B uses the news scores based on the IMF news. In order to avoid multi-collinearity, the regression includes only one news score sequence at a time. That is, four regressions are performed to obtain the coefficients of the contemporaneous, 1-, 2- and 3-day lagged news variables. The coefficients for other explanatory variables and the adjusted R-squared are based on the regressions with a contemporaneous news score.

Panel A: ECB News

	NonFin	**Fin**	**SovX**
Equity Return	0.483***	0.761***	0.512***
Market Funding Risk	0.002	-0.000	0.003
Investment Grade	207.598***	212.981**	139.864
High Yield	-8.608***	-4.343	-1.196
Term Premium	0.063*	0.149**	0.025
Volatility Premium	0.000	-0.005***	-0.001*
FX Risk	21.967	12.008	50.095**
Counterparty Risk	-0.175***	-0.262***	-0.151***
Market Liquidity Risk	-0.025***	-0.002*	-0.023***
Trading Return	0.016	0.010***	0.003
News ECB	0.000	0.025***	0.022***
News ECB (Lag 1)	-0.003	0.020***	0.022***
News ECB (Lag 2)	-0.000	0.024***	0.015**
News ECB (Lag 3)	0.000	0.026***	0.015**
Constant	0.075***	0.044***	0.338***
N	2,155	2,155	1,095
Adjusted R^2	0.190	0.167	0.147

Panel B: IMF News

	NonFin	**Fin**	**SovX**
Equity Return	0.479***	0.768***	0.542***
Market Funding Risk	0.002	-0.001	0.003
Investment Grade	205.083***	219.686**	158.577
High Yield	-8.653***	-4.114	-0.690
Term Premium	0.060*	0.152**	0.015
Volatility Premium	0.000	-0.005***	-0.001*
FX Risk	22.846	9.342	46.538**
Counterparty Risk	-0.173***	-0.262***	-0.158***
Market Liquidity Risk	-0.025***	-0.002*	-0.023***
Trading Return	0.016	0.010***	0.001
News IMF	0.025***	0.001	0.009
News IMF (Lag 1)	0.026***	0.003	0.010
News IMF (Lag 2)	0.022***	-0.003	0.004
News IMF (Lag 3)	0.024***	0.002	0.011
Constant	0.073***	0.048***	0.348***
N	2,155	2,155	1,095
Adjusted R^2	0.197	0.160	0.139

Table 2.7. Forecasting: Risk Reversal

The following table reports the time series regression with Newey-West standard errors for the option risk reversal on the lagged basket-index spreads extracted from the non-financial, financial and sovereign sectors. The risk reversal is constructed using OTM put and call options on the STOXX 50 stock index, with 1-month maturity and a moneyness of 25. The independent variables include 1-day lagged risk reversal, 1-day lagged basket-index spreads, 1-day lagged government news score and an interaction term between the spreads and the news score. Panel A uses the news scores based on the ECB news, and panel B uses the news scores based on the IMF news. The sample period is from January 2006 to April 2014 for the non-financial and financial sector, and from September 2009 to April 2014 for the sovereign sector. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

Panel A: ECB News	**NonFin**	**Fin**	**SovX**
Risk Reversal (Lag 1)	0.586***	0.594***	0.712***
Spread (Lag 1)	4.569***	2.163***	3.539***
News ECB (Lag 1)	-0.080	-0.063	-0.172
Spread(Lag 1)* News ECB(Lag 1)	-0.018	-1.124**	-3.280***
Constant	-0.363***	-0.424***	-0.431***
N	2,155	2,155	1,095
R^2	0.369	0.364	0.518
Adjusted R^2	0.367	0.363	0.516

Panel B: IMF News	**NonFin**	**Fin**	**SovX**
Risk Reversal (Lag 1)	0.586***	0.595***	0.713***
Spread (Lag 1)	4.677***	2.015***	3.181***
News IMF (Lag 1)	-0.164	-0.036	-0.153
Spread(Lag 1)* News IMF(Lag 1)	-1.716	-0.081**	-0.867**
Constant	-0.343***	-0.417***	-0.403***
N	2,154	2,154	1,094
R^2	0.369	0.364	0.518
Adjusted R^2	0.367	0.363	0.516

Table 2.8. Predicting Risk Reversal: Out-Of-Sample

The following table reports the results of the out-of-sample test on the predicting power of the basket-index spreads. The dependent variable is the option risk reversal. The out-of-sample test is performed on a rolling-window forecasting with a window size of 180 days. The first row reports the estimated coefficient of the basket-index spreads. The lower part of the table reports the Clark and West F-test statistics and t-statistics between the competing model and the benchmark model. The second and third rows compare the predictability of the spread measure against the first benchmark model, the random walk process. The last two rows report the F-test and t-statistics on the competing model against the second benchmark model, the AR(1) process. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	NonFin	**Fin**	**SovX**
$\hat{\gamma}$	0.786	1.578	2.989
Clark & West F- Test			
F-stats: RW	15.85	15.64	15.99
t-stats: RW	4.91***	4.84***	5.16***
F-stats: AR(1)	0.175	0.157	0.131
t-stats: AR(1)	3.36***	2.01**	2.61***

Table 2.9. Fama-MacBeth Cross Sectional Regression

The following table reports the Fama-MacBeth cross-sectional regression. The dependent variable is the 25 European portfolios formed on size and book-to-market. The independent variables are equity market returns, the firm size, the high minus low, and the CDS basket-index spreads. The top, middle, and bottom panels report the results using the spreads extracted from the non-financial sector, financial sector and sovereign sector respectively. The sample period is from January 2006 to April 2014 for the non-financial and financial sector, and from September 2009 to April 2014 for the sovereign sector. The first four columns report the factor loading on each risk factor. The second four columns report the price of the corresponding risk factor. The t-statistics are reported in the square brackets. The last three columns report the adjusted R-squared, the Chi-square statistics and the HJ distance test. The null for the Chi-square test and the HJ distance test is that: there is a joint zero pricing error.

	b_{mkt}	b_{size}	b_{hml}	b_{sprd}	λ_{mkt}	λ_{size}	λ_{hml}	λ_{sprd}	R^2	χ^2	HJ
NonFin	0.04	0.03	-0.04	-0.12	0.68	0.04	-0.04	-0.14	0.69	**4.61**	**0.76**
	[4.00]	[1.35]	[-1.69]	[-1.75]	[2.18]	[0.40]	[-0.37]	[-1.18]			
Fin	0.04	0.00	-0.10	0.20	0.70	0.06	-0.06	0.57	0.59	**6.19**	**0.76**
	[4.72]	[0.12]	[-5.42]	[3.03]	[2.35]	[0.57]	[-0.61]	[2.59]			
SovX	0.07	0.02	-0.18	0.54	0.80	0.06	-0.28	0.32	0.67	**4.84**	**0.88**
	[11.29]	[1.21]	[-9.84]	[4.98]	[4.03]	[0.79]	[-2.21]	[3.01]			

Chapter 3

Media Content and Sovereign Credit Risk[1]

3.1 Introduction

Does the linguistic content of news items impact sovereign credit risk? Does it improve our understanding of countries' fundamentals? Does it proxy for investor sentiment? We investigate these questions by using an extensive sovereign credit default swap (CDS) dataset and the ratings of news content (i.e., sentiment) from Thomson Reuters News Analytics (TRNA). We consider sovereign CDS contracts as a proxy for country specific credit risk. These represent an insurance contract against sovereign default or restructuring events and are generally more liquid than the underlying bond. In the TRNA database news items are rated in terms of sentiment (positive or negative) in real time using a highly sophisticated neural network which provides an improvement over traditional approaches (such as bag-of-words). Furthermore, TRNA reflects a more accurate representation of the news set used by actual investors, as it is a commercial product that is sold directly to subscribers.

Numerous studies have explored sovereign credit risk and its determinants, which include Acharya, Drechsler, and Schnabl (2014) Edwards (1984, 1986); Berg and Sachs (1988); Boehmer and Megginson (1990); Duffie, Pedersen, and Singleton (2003), Longstaff, Pan, Pedersen, and Singleton (2011); Pan and Singleton (2008); Remolona, Scatigna, and Wu (2007); Jeanneret (2015) and Badaoui, Cathcart, and El-Jahel (2013); Monfort and Renne (2014). In particular Longstaff, Pan, Pedersen, and Singleton (2011) highlight the high level of commonality in sovereign credit spreads and find that they are explained along with their components: default risk and risk premium by global factors to a greater extent than country-specific fundamentals.[2] Coupled with global factors, behavioural measures such as market sentiment have also been found to influence sovereign credit risk (Georgoutsos and Migiakis, 2013; Tang and Yan, 2013; Apergis, Lau, and Yarovaya, 2016).[3] To the best of our knowledge, the impact of media tone (sentiment) on sovereign credit risk has yet to be explored.

The ability of media content to impact equity markets has recently received considerable attention in the literature. In particular, Tetlock (2007) examines how qualitative information is incorporated

[1]This chapter is based on Cathcart, Gotthelf, Uhl, and Shi (2016).

[2]Risk premium is defined as distress risk, i.e., it is the premium associated with the unpredictable variation in the arrival rate of credit events.

[3]The most significant variables for CDS spreads have been found to be the US stock and high yield markets and the VIX index.

in aggregate market valuations and Garcia (2013) shows that the predictability of stock returns using news content is concentrated in recessions. Dougal, Engelberg, Garcia, and Christopher (2012) identify a causal relationship between financial reporting and stock market performance. Engelberg and Parsons (2011) find that local media coverage strongly predicts local trading, and that local trading is strongly related to the timing of local reporting. Uhl, Pedersen, and Malitius (2015) find a longer-run effect of news sentiment on equities with weekly data. Tetlock, Saar-Tsechansky, and Macskassy (2008) examine the impact of negative words on individual S&P 500 firms and Hillert, Jacobs, and Müller (2014) find that firms particularly covered by media exhibit stronger momentum and that this effect depends on media tone. Hence, media coverage exacerbates investor biases.

To investigate the role of media in the sovereign CDS market, we first construct a global "news sentiment" variable from TRNA by filtering according to global debt markets news, US news and regional news pertaining to Europe, Latin America and Asia. The motivation for a global "news sentiment" variable is built on results established in the literature which are suggestive of increasing economic integration across countries, growing dependence on global markets and a spill-over effect from the US to other sovereign countries.[4] Second, we decompose the CDS spread into risk premium and default risk components for each country using an affine sovereign credit risk model in line with Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2011). This allows for a better understanding of the role of media and helps shed light on whether media tone could convey information about countries' fundamentals. Finally, we conduct a principal component analysis, fixed effect panel regression and panel vector autoregressive model (VAR). Panel VARs are able to capture the dynamic interdependencies present in the data using a minimal set of restrictions. They also allow impulse response analyses to be constructed in a relatively straightforward way.

Several results emerge from our analysis. First, we find, in line with Longstaff, Pan, Pedersen, and Singleton (2011) a high level of commonality in sovereign risk, with the first principle component explaining 62% of the CDS spread returns. We also find that the commonality is mainly driven by the default risk component and to a lesser extent by the risk premium. The first principal component explains 57% and 14% of the default risk component and risk premium returns respectively. Furthermore, the first principle component of CDS, default risk component and risk premium returns has a correlation of $-15, 23\%$, -15.14% and -12.13% respectively with the news sentiment variable. Thus, sovereign credit risk appears to be connected to media content, with the link being stronger for the default risk component than for the risk premium.

Second, we find that news sentiment explains sovereign credit risk. Specifically, we regress CDS returns on the news sentiment variable in a fixed effect panel and control for local and global variables. The news sentiment variable has significant explanatory power for CDS returns. The relationship between CDS returns and the news sentiment variable is negative, implying an improvement in me-

[4] Longstaff, Pan, Pedersen, and Singleton (2011) document a strong relation between CDS spreads and global variables, in particular the VIX and the US stock market.

dia tone (positive) decreases returns. We repeat the same exercise for the default risk component and risk premium. We find that the news sentiment variable is a significant driver of the default risk component; however, it loses significance for the risk premium.

Third, using a panel VAR, we show that the news sentiment factor predicts CDS returns. This effect is robust to controls for autocorrelation and determinants of CDS returns and partially reverses within five weeks. Media tone could act as a proxy for investor sentiment, a novel informational channel, or could be a mixture of both. On the one hand, sentiment theory postulates that short horizon returns will be reversed in the long run. On the other hand, the information theory predicts that they will persist indefinitely. A mixture of noise and information will correspond to a partial reversal and will lend support for theories of over- or underreaction to news in line with Daniel, Hirshleifer, and Subrahmanyam (1998).

In order to shed more light on the present issue, we run the same return predictability regressions on both the default and risk premium components of CDS spreads. We find news sentiment predicts both components' returns significantly. However, the effect on the default component partially reverses over the following five weeks whereas the effect on the risk premium reverses fully. This result confirms the idea that media content is a mixture of noise and information. The informational channel is more likely to impact the default component and lead to reassessments of the fundamentals of sovereign economies. The noise channel is more likely to impact the risk premium and induce a temporary change in investors' appetite for credit exposure. Overall, our results support a behavioural story and the theories of over- or underreaction. In particular, the behavioural economics' literature has shown that sentiment can move aggregate financial quantities; see Hirshleifer (2001) for a survey on this topic. It has also been documented that behavioural psychological investor biases could lead to overreaction as in Daniel, Hirshleifer, and Subrahmanyam (1998).

In summary, our work is the first to show that media tone explains and predicts CDS returns, conveys information about countries' fundamentals and to demonstrate that the sovereign credit market is subject to behavioural biases. Our paper contributes to two strands of literature: sovereign credit risk and its determinants as well as the role of media in financial markets. It is closely related to the work of Longstaff, Pan, Pedersen, and Singleton (2011), Remolona, Scatigna, and Wu (2007) and Pan and Singleton (2008) with respect to sovereign credit risk. It is also closely related to Tetlock (2007) and Garcia (2013) with respect to investigating the impact of media content on equity return predictability.

The layout of the paper is as follows. In Section 3.2 we describe the CDS data, the decomposition of the CDS spread into its default risk component and risk premia. We also describe the Thomson Reuters News Analytics. Section 3.3 focuses on the principle component analysis. Section 3.4 presents the regression analysis and results. Section 3.5 explores the impact of media tone on the predictability of returns and their informational content. Section 3.6 concludes.

3.2 Data

This section describes the CDS and Thomson Reuters News Analytics datasets. We also present descriptive statistics as well as the decomposition methodology for the default and risk premium components.

3.2.1 CDS Data

A CDS is an insurance contract that protects the holder against the default of the underlying reference entity. The buyer pays an annuity premium to the protection seller at a quarterly or bi-yearly frequency. If a default were to occur, the CDS buyer then receives a payment from the CDS seller. This payment amounts to the difference between the notional principal and the loss upon the default of the reference entity.

We use sovereign CDS contracts as a proxy for country specific credit risk. Several studies have highlighted the merits of using CDS contracts (rather than bonds) to capture the default risk of the underlying entities (Augustin and Tédongap, 2016; Augustin, Subrahmanyam, Tang, and Wang, 2014; Pan and Singleton, 2008; Longstaff, Pan, Pedersen, and Singleton, 2011; Fontana and Scheicher, 2016). There are numerous reasons for this; sovereign CDS contracts are not subject to the complex guarantees and options which are typically embedded in government bonds. Therefore, it is easier to infer the default risk of the underlying from CDS contracts. Government bond yields are also impacted by taxation standards and the legislation procedures of the issuing countries. This is problematic considering that the countries in our sample have different standards in this regard, so using CDS contracts ensures comparability. Finally, the CDS market offers better liquidity than the underlying bonds for many countries.

We focus on contracts with a maturity of five years. This maturity is the most liquid in the CDS term structure. Furthermore, we specify the clauses as senior debt for the government bonds that underlie the sovereign CDS contracts. Senior debt entitles the bond holder to seniority (over subordinate debt) when claiming losses, given that the bond issuer defaults on both senior and subordinate bonds. Senior debt contains less credit risk and has a better recovery rate. The market for sovereign CDS contracts written on senior debt is also more liquid than the market for subordinate debt. We consider the recovery criteria for the underlying government debt contracts as 'NO Restructuring', and the notional is expressed in US dollars.

Our dataset is downloaded from Markit. The sample period is from January 2003 until April 2014.

For missing data points, we interpolate using the credit term structure (the four and seven year maturities). Additionally, we winsorise the data by replacing extreme outliers with cut-off points for observations in the 1st and 99th percentile. We consider developed and emerging countries from different geographical regions. Our sample consists of Bulgaria, Brazil, Chile, China, Colombia, Croatia, Israel, Japan, Korea, Malaysia, Mexico, Panama, Philippines, Poland, Qatar, Romania, Russia, Slovak, South of Africa, Ukraine and Venezuela.

Table 3.1 provides summary statistics. All sovereign spreads are expressed in basis points. We observe a great deal of cross-sectional variation in our sample. Among the countries considered, Japan has the lowest mean CDS spread (41.17 basis points) and smallest standard deviation (37.94). This is to be expected, as Japan is considered a safe heaven and the most developed country out of the 21 sovereigns we study. At the other end of the spectrum, Venezuela has the highest mean spread of 825.94 basis points. Ukraine is second with a mean of 660.01 basis points. The spreads of both countries are also highly volatile, with standard deviations of 703.63 and 547.66 respectively. On a country specific level, we also find a great deal of dispersion in the time series. For instance, the sovereign spread for Ukraine ranges from 126.62 to 5288.98 basis points, whilst China's CDS spread varies from 9.35 to 277.31 basis points during the same sample period.

3.2.2 Decomposing the CDS Spread

We decompose the sovereign CDS spread into two components: a default risk component and a risk premium component. The risk premium is defined as the unpredictable variation in the arrival rate λ of a credit event.[5] We adopt an affine credit risk valuation model and follow closely Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2011)'s methodology for decomposing CDS spreads.

In particular, the spread of a M-year CDS contract is given by the following expression.

$$CDS_t^Q(M) = \frac{2(1-R^Q)\int_t^{t+M} E_t^Q[\lambda e^{-\int_t^u (r_s+\lambda_s)ds}]du}{\sum_{j=1}^{2M}[E_t^Q e^{-\int_t^{t+j/2}(r_s+\lambda_s)ds}]} \tag{3.1}$$

Where E^Q is the expectation under the risk-neutral measure, R^Q is the risk-neutral fractional recovery rate on the underlying given that a relevant credit event occurs (i.e., a default), r_t is the risk-less rate, and λ_t is the risk-neutral intensity (i.e., the arrival rate of a credit event). The numerator of equation (3.1) represents the present value of the contingent payment made by the protection seller to the protection buyer in light of a credit event. The denominator represents the present value of the M-year semi-annual annuity, conditional on there not having been a credit event. The discount

[5] The risk premium in this context is what we call distress risk. This is different from the jump-at-event risk premium associated with a surprise jump in price at the moment of a credit event.

rate $r_t + \lambda_t$ reflects the survival-dependent nature of the CDS contract.

We assume the behaviour of the default intensity λ follows a log-normal distribution governed by parameter κ, θ, σ. As for the notation, superscripts Q and P are used to denote the parameters of the intensity process λ under the risk-neutral and objective measure, respectively. In particular, equation (3.2) shows the default intensity dynamics under the risk-neutral measure Q, whilst equation (3.3) shows the dynamics under the objective measure P.

$$d \ln \lambda_t = \kappa^Q(\theta^Q - \ln \lambda_t)dt + \sigma_\lambda dB_t^Q. \tag{3.2}$$

$$d \ln \lambda_t = \kappa^P(\theta^P - \ln \lambda_t)dt + \sigma_\lambda dB_t^P. \tag{3.3}$$

We assume that r_t and λ_t are independent, the market CDS spread, is now given by equation (3.4),

$$CDS_t^Q(M) = \frac{2(1-R^Q)\int_t^{t+M} D(t,u)E_t^Q[\lambda e^{-\int_t^u \lambda_s ds}]du}{\sum_{j=1}^{2M} D(t,t+j/2)[E_t^Q e^{-\int_t^{t+j/2} \lambda_s ds}]} \tag{3.4}$$

where $D(t,u)$ is the price of a default-free zero-coupon bond, issued at date t and maturing at date u. The corresponding CDS spread implied by the P objective process $CDS_t^P(M)$ is given by equation (3.5) where E^P is the expectation under the objective measure.

$$CDS_t^P(M) = \frac{2(1-R^Q)\int_t^{t+M} D(t,u)E_t^P[\lambda e^{-\int_t^u \lambda_s ds}]du}{\sum_{j=1}^{2M} D(t,t+j/2)[E_t^P e^{-\int_t^{t+j/2} \lambda_s ds}]} \tag{3.5}$$

First, in order to price said security, we take the expectation with respect to the distribution of λ under the risk-neutral process. We bootstrap the hazard rate from the sovereign CDS spread we observe in the market, and we obtain the parameters $(\kappa^Q, \theta^Q, \sigma)$ under the risk-neutral setting based on equation (3.4). Second, to estimate the parameters under the physical measure (κ^P, θ^P), we take the expectation with respect to the probability distribution implied by the objective process. We apply the maximum likelihood estimator based on the term structure of sovereign credit spreads using equation (3.5). For the term structure, we use 3-year, 5-year and 7-year CDS spreads. Unlike Longstaff, Pan, Pedersen, and Singleton (2011), we assume the 5-year sovereign CDS is perfectly priced, and the 3-year and the 7-year contracts are priced with a normally distributed error of mean zero and standard deviation $\sigma_\epsilon(3)$ and $\sigma_\epsilon(5)$. Furthermore, we use weekly observations rather than monthly.

These parameters backed out from the two processes may differ from one another. However, the two are related by the "market price of risk" as shown in equation (3.6). Equation (3.7) displays the connection between the parameters as the probability distribution shifts from P to Q.

$$\eta_t = \delta_0 + \delta_1 \ln \lambda_t \tag{3.6}$$

$$\begin{aligned} \kappa^Q &= \kappa^P + \delta_1 \sigma_\lambda \\ \kappa^Q \theta^Q &= \kappa^P \theta^P - \delta_0 \sigma_\lambda \end{aligned} \tag{3.7}$$

For $\delta_0 = 0$ and $\delta_1 = 0$, the risk-neutral Q process coincides with the objective process P, since the market price of "distress" risk η that is associated with unpredictable variation in λ_t is zero.

However, the expectations in expression (3.4) and (3.5) have no closed form solutions. Thus, we compute these expectations numerically by using an implicit finite-difference method to solve the Feynman-Kac partial differential equation. Once we obtain the parameters estimates under the physical measure, we then estimate the sovereign CDS spreads under the physical measure by using equation (3.5). The risk premium is therefore defined as the observed market sovereign CDS spread minus the CDS spread estimated under the P distribution. Finally, we calculate the default risk component of CDS spread as the difference between the CDS spread under the Q distribution and the risk premium.

We perform the credit risk decomposition for all 21 countries in our sample. The summary statistics pertaining to the credit risk premium are reported in Table 3.3. As can be seen, there is a great deal of dispersion within our sample; Japan has the lowest average risk premium of 14.22 basis points whilst Pakistan has a mean of 104.75 basis points. The same can be said for the standard deviation. Ukraine has the largest with a variation of 349.37.[6]

3.2.3 News Sentiment

The second pillar of our study concerns the sentiment that is inherent in newspaper articles. News sentiment is extracted from the Thomson Reuters News Analytics database. The provider rates media content coming from its own database (all articles published by Thomson Reuters globally) according to various topic classifiers using highly sophisticated Natural Language Processing Techniques (NLP).

The database generates a series of metadata for each news article, the most important of which are described in the following based upon the work of Smales (2014): the identifier links a piece of news to a given topic classifier, while the timestamp indicates the arrival rate of media content. The sentiment of news articles is measured in discrete time, where given content is attributed a score

[6] The summary statistics results are very much in line with the findings of Longstaff, Pan, Pedersen, and Singleton (2011).

ranging between positive (+1), negative (-1) and neutral (0).

Sentiment scores are determined by an algorithm that works in three steps: In the first step, a given text is pre-processed. Given media content is broken down into basic linguistic elements commonly known as parts of speech. This includes structural elements such as sentences and phrases, as well as verbs, nouns and adjectives. In the second step, items are connected into sentiment-bearing phrases, usually consisting of adjective-noun combinations.

In the final step, the said phrases are then subject to feature extracting, taking into account a series of predetermined positive and negative keywords and phrases. The dictionary used in this stage contains nearly 16,000 words, while the lexicon features almost 2,500 phrases (Cahan, Cahan, Lee, and Nguyen, 2015). These classifications are based on human coders and are incorporated into a learning algorithm. This thereby improves the traditional "bag-of-words" approach by better identifying sentiment within a context where the order of words matters, and sets our data apart. Another unique advantage of the database is highlighted by Dzielinski (2011). Reuters has strict style rules in place regarding the reporting of news content, and carefully monitors all contributions. This mitigates the influence of the authors own option on the news sentiment data, and places the focus on the dynamics of a given region or asset class itself.

This data is available on a high frequency basis, but for the purpose of our paper is aggregated on a weekly basis from 2003 onwards. We construct a global "news sentiment" variable from TRNA by filtering according to global debt markets news, U.S. news and regional news pertaining to Europe, Latin America and Asia. We take the average of all sentiment scores in order to create a global news sentiment variable.

3.3 Principal Component Analysis

Existing literature has shown that a large degree of commonality and co-movement exists in sovereign credit spreads (Ang and Longstaff, 2013; Longstaff, Pan, Pedersen, and Singleton, 2011; Pan and Singleton, 2008). Motivated by this evidence, we explore the potential sources of this kind of variation, with a particular focus on the impact of media content. We perform a principal component analysis (PCA) on the returns of sovereign CDS spreads, the default risk component, as well as the risk premium. In the following, we use simple returns.[7] We analyse the correlation coefficients between the first three latent principal components and our variable of interest: news sentiment. We also use the VIX risk premium and the US equity market excess return as comparison benchmarks.[8]

[7] Simple returns are approximated by $Y_{i,t} = \frac{CDS_{i,t} - CDS_{i,t-1}}{CDS_{i,t-1}}$ where i stands for CDS spread, default risk component and risk premium respectively.

[8] Please refer to the Appendix B.2 for a definition of the VIX risk premium and U.S equity excess return. We also calculate the correlation between our principal factors with changes in the VIX index as in Longstaff, Pan, Pedersen,

These latter variables capture the documented influence of the U.S economy on other regions of the world.

The results for the PCA and correlation analysis are reported in Table 3.4. The PCA is based on the correlation matrix of weekly returns of CDS and both components: default and risk premium. We calculate the pair-wise correlation between two countries whenever observations are available for both. This correlation matrix is then used to estimate the principal components.

In the top part of Table 3.4, the first column reports the proportion of variations explained by the first three components respectively. The second column reports the cumulative proportion of variation explained by the corresponding components. We find that the first component explains around 62.38 percent of total variation in CDS returns across all countries. Cumulatively, all three components explain approximately 73.57 percent of sovereign CDS returns. The PCA analysis echoes the findings in Longstaff, Pan, Pedersen, and Singleton (2011), indicating that there is strong commonality in the cross-sectional sovereign spread movements. In the next step, we report the correlations between the time series of the first three principal components and our variables of interest (news sentiment, VIX risk premium, US excess return) for the sample period. We find a negative correlation between the first principle component and all three variables. These are all significant at the 1 percent level. In particular, the correlation between the first principle component and news sentiment, VIX risk premium and US excess returns is -15.23, -29.57 and 15.04 percent respectively.

In the second part of Table 3.4, the PCA and correlation analysis for the default component is reported. The first principal component explains 57.19 percent of the total variation in the return of the default premium. This is slightly lower than the proportion explained by the first principal component for CDS returns. All three components cumulatively explain 68.52 percent of the given variation. The first component is negatively and significantly correlated with all three risk factors. The correlation coefficients are -15.14, -28.43 and -14.49 percent for news sentiment, the VIX risk factor and US excess stock returns, respectively.

The third part of Table 3.4 shows the principal component and correlation coefficients for the risk premium. Here, the first principal component explains 14.07 percent of the cross-sectional variation in the CDS risk premium. Cumulatively, all three principal components explain 27.81 percent of the risk premium movements. Compared to our previous analysis, there is less commonality in the cross-sectional movement of the CDS risk premium. Turning to the correlation coefficient analysis, the first component still illustrates a negative correlation of -12.13, -17.96 and -14.09 percent with news sentiment, the VIX risk premium and US excess stock returns respectively. These are all significant at the 1 percent level. However, the correlation levels between risk premium and our three variables of interest are smaller than the correlation levels for the CDS return and default risk

and Singleton (2011). The correlation between the changes in the VIX index and the first principal component is as high as 64 percent and significant at the 1% level.

component.

The PCA and correlation analysis suggest that there is commonality in the variation of sovereign CDS returns and both components, albeit to a lesser extent with the risk premium. Furthermore, we find that the principal sources of return movements are significantly correlated with the news sentiment variable with comparable correlation levels to the benchmark variables; the VIX risk premium and US excess stock returns.

3.4 Regression Analysis

We perform a regression analysis to explore the role of media content as a driver of sovereign CDS, default risk and risk premium components' returns. We opt for a panel regression with fixed effects to study the cross-sectional and time series dynamics. The panel regressions include our media content measure as well as various control variables for robustness purposes. For these control variables, we distinguish between three categories of explanatory variables: global risk factors, local variables and sovereign spreads.[9]

Global Risk Factors

We use the excess returns of the US stock market as an equity market variable. To capture the conditions in the US fixed income market, we construct a treasury market variable defined as the return of the five-year constant maturity Treasury rate from the US Federal Reserve. Furthermore, we consider two variables from the US corporate credit market: the investment grade and high yield spreads. The investment grade variable is taken as the return of the difference between five-year BBB- and AAA-rated corporate effective yields. The high yield spread is calculated as the return of the difference between BB- and BBB-rated corporate bond yields. For the equity risk premium, we construct the volatility risk premium as the VIX index minus the one-month implied volatility of the S&P 500 index. For credit market, we consider the term premium, which is the yield differential between 10-year USD Interest Rate Swap Rate and the one-month USD Libor rate. This variable aims to capture the potential influence of flight-to-quality (Pan and Singleton, 2008; Augustin and Tédongap, 2016; Kallestrup, Lando, and Murgoci, 2016).

Local Risk Factors

One cannot neglect the importance of local economic conditions in establishing a sovereign's creditability, which is in turn reflected in CDS pricing. Next to global risk factors, we therefore also include two local risk factors which can affect the sovereign's ability to repay its debt: exchange rate returns and local stock returns.

[9]For variable construction see Appendix B.2.

Sovereign Spreads

We take into account the influence of regional and global CDS spread movements by incorporating two sovereign spread factors: a regional spread and a global spread. Our sample is divided into four categories according to geographical location: Latin America, Asia, Europe and the Middle East/Other. The variables are constructed in the following steps: first, for each sovereign in our sample, two average CDS spreads are computed: the average regional spread and the average global spread. The average regional spread is the mean CDS spread for the other countries in the same region. The average global spread is the mean CDS spread for the countries in the other three regions. We then regress the return of the average regional spread (global spread) on all global risk factors. The residuals are taken, which serve as additional explanatory variables for the regression analysis.

3.4.1 Methodology & Regression Results

Main Results

We perform a panel regression as shown in equation (3.8), for the returns of CDS spreads, default risk and risk premium components denoted by $Y_{i,t}$ respectively. We control for heteroskedasticity by using the Halbert White (1980) standard errors. Fixed effects are also included in the regression to ensure that country specific characteristics are considered. We perform regressions on the weekly returns of the aforementioned components, ensuring that all variables are stationary for the panel regression.

$$\begin{aligned} Y_{i,t} = \alpha_i &+ \beta_{i,1} US\ stock_t + \beta_{i,2} Vol\ prem_t + \beta_{i,3} Term\ prem_t + \beta_{i,4} Treasury_t \\ &+ \beta_{i,5} Investment\ grade_t + \beta_{i,6} High\ yield_t + \beta_{i,7} Exchange\ return_{i,t} \\ &+ \beta_{i,8} Stock\ return_{i,t} + \beta_{i,9} Regional\ spread_{i,t} + \beta_{i,10} Global\ spread_{i,t} \\ &+ \beta_{i,11} News\ sentiment_t + \epsilon_{i,t} \end{aligned} \tag{3.8}$$

We report the results of equation (3.8) in Table 3.5. These consist of the robust coefficient estimates, the adjusted R-squared as well as the number of observations for each regression. The first column reports the estimation for the sovereign CDS returns. News sentiment alongside all global risk factors is shown to be a highly significant explanatory variable for sovereign CDS returns, with the relationship being negative. Optimism in the news results in a reduction of the credit risk associated with sovereign debt markets. As has been mentioned in the previous section, our measure of news sentiment is global. The high degree of relevance and significance of this factor is in line with previous work highlighting the importance of global risk factors for sovereign credit default swaps.

With regard to the local variables, both domestic exchange returns and stock index returns tend to have a negative impact on the sovereign credit returns. However, the impact of the exchange rate return is not statistically significant. With respect to sovereign spreads, it is reasonable to expect a sovereign's insurance costs to increase when the region experiences an economic shock or when there is a global shock. We find a positive relationship between the regional sovereign spreads and the country's credit spread returns. Similar results were also found for global sovereign spreads. The Adjusted R-squared is 66.3, which indicates that our variables explain a considerable proportion of the variation in sovereign CDS returns.

The regression on the default risk component returns also shows a highly significant negative relationship with the news sentiment variable. An increase in the tone of media reporting therefore results in a decline in the default risk. Furthermore, news sentiment has an even stronger impact on the default component with a coefficient of -0.137 compared to -0.122, for the sovereign CDS return. Research has shown that the media consistently affects consumer's perception of the state of the economy (Doms and Morin, 2004). This typically occurs through multiple channels, including the informational aspect that news conveys with the latest economic data releases. Importantly, the tone of media reporting generates a signal about the global and local economy for consumers. Thus, as the news sentiment shifts, investors revise their expectations regarding the economy and in turn reassess the fundamental components of sovereign credit risk. Most of the global risk factors except the term premium are statistically significant at the 1 percent level. The relation between the default risk component and the global factors confirms the existing evidence of increasing economic integration and dependence on global capital markets and a spill-over effect from the US to other sovereign economies.

The regression on the risk premium returns, however, shows that it is not impacted by news sentiment in a significant manner. The respective coefficient is -0.025. The negative sign suggests that an improvement in the media tone does reduce the uncertainty regarding the potential default event arrival. However, the impact of news sentiment is much smaller than on CDS returns and the default component, and the coefficient is not statistically significant. Instead, other global factors such as the volatility premium, term premium, high yield spread, global spread and treasury market play a role in explaining risk premium returns. The relation of risk premium returns with global factors can be explained by the presence of global investors. However, overall our variables do not seem to be able to capture much of the variation in the risk premium returns.

Additional Results

In the following, we perform various robustness checks. We run the same panel regressions for the CDS, default risk component and risk premium returns (equation 3.8); however, we control for the impact of the US and EU sovereign recessions. We introduce a dummy variable equal to one from September, 2008 to March, 2009, and from July 2011 to April 2014. The respective recession periods are based on the business cycle indicator reported in CEPR. The results remain consistent and the significance of the global risk factors and news sentiment variable are unaffected.[10]

Having established our results on an aggregate level, we perform individual country regression on each country's sovereign CDS spreads, default risk and risk premium returns using equation (3.8). The results are aligned and consistent with the panel regression. Hence, the impact of news sentiment not only holds at an aggregate level but also at individual levels. The regression results for individual countries' sovereign CDS returns are reported in appendix Table B.1.

We check the validity of our global news sentiment indicator by constructing two different news sentiment variables: a regional variable and a purely global variable. For the regional news sentiment, only the local regional news where a given sovereign is located is included. Our sample is divided into four geographical regions; Europe, Latin America, Asia and Middle East/Other. We run individual country regression (CDS returns and components returns) for all countries based in the same region using the respective regional sentiment variable. We report the results for the first three regions but we exclude countries located in Middle East/Other due to lack of local news volume. The regional news sentiment variables are not significant for all countries. Also, on average the economic significance is lower than for the global new sentiment variable. The regression results for CDS returns are reported in Appendix B.1 Table B.3 and Table B.4.

For the purely global sentiment variable, we remove the respective regional news and the global debt news component (as it might contain regional debt news) from the new sentiment variable and run similar individual countries regression for all countries based in the same regions using the respective pure global sentiment variable without the aforementioned regional news. Overall, the results remain consistent with the original news sentiment variable. This suggests that global and US news play an important role in sovereign CDS movements. The regression results for CDS returns are reported in Appendix B.1 Table B.5 and Table B.6.[11]

3.5 Informational Content of News Sentiment

In the previous section, we established that news sentiment is a highly significant explanatory variable for the credit default swap and default risk component returns. The impact on the default risk component in particular indicates that the news sentiment variable might contain new information about countries' fundamentals. In the following, we examine further the content of the news sentiment variable and explore its predictability. We also attempt to establish causality. It has been noted by Engelberg and Parsons (2011) that separating the causal impact of media reporting on asset prices is no easy feat. This is particularly true because news coverage does not occur at

[10] Results are available upon request.

[11] The results for the default risk and risk premium components for the individual regressions with the news sentiment, regional and purely global sentiment variables are available from the authors upon request.

random. It is hard to know whether it was the media which garnered a reaction by markets, or the event about which is reported itself.

We use a panel vector autoregression (panel VAR) model and the associated impulse response functions for the returns of CDS spreads, as well as for the returns of the default component and the risk premium. We also explore the existence of a feedback loop. In our set-up, the endogenous variables are CDS returns (default component and risk premiums returns) denoted by $Y_{i,t}$ and news sentiment. The exogenous variables are the determinants of CDS returns established in the previous section; global risk factors, sovereign spreads and local variables denoted by $X_{k,t}$, wherein $k = 1, ...10$ control variables. We use five lags of the news sentiment variable (five weeks of past information in our setting). This lag length was chosen in accordance with the Bayesian information criteria and is the optimal number in this framework. We control for both heteroskedasticity and autocorrelation. The return equation for the first panel VAR is as follow

$$Y_{i,t} = \alpha_i + \beta_{i,k} X_{k,t-1} + \sum_{l=1}^{5} \delta_{i,l} Y_{i,t-l} + \sum_{l=1}^{5} \gamma_{i,l} News_{t-l} + \epsilon_{i,t} \tag{3.9}$$

It is worth noting that a panel VAR contains a cross-sectional dimension as represented in the i of the $Y_{i,t}$ series. Hence, such a cross-sectional panel will allow us to study both the dynamic inter-dependencies in the $Y_{i,t}$ as well as the static inter-dependence of the error term $\epsilon_{i,t}$. The standard VAR model would be incapable of showing the dynamic inter-dependencies by assuming sector homogeneity at a-priori level. Furthermore, the main feature which distinguishes a panel VAR from traditional VAR models is that it allows for the cross-sectional heterogeneity assumption, whilst most VAR models assume cross-sectional homogeneity, see Canova and Ciccarelli (2013). The results for equation (3.9) are reported in Table 3.6. The results for CDS returns are presented in the first column. News sentiment has a statistically significant negative relationship at the 1% level for the first two lags. For the third and fourth lag, news sentiment remains statistically significant at the 5% level, but then has a positive coefficient as the effect reverses. In the fifth week, the effect vanishes, and news sentiment no longer bears significant explanatory power for CDS returns. We perform an F-Test with null hypothesis that the sum of the coefficients corresponding to the five lags of news sentiment is equal to zero. The F-statistic for the sovereign CDS returns is 7.37 with a p-value of 0.006. This test allows a rejection of the null hypothesis of a full reversal at the relevant significance levels. This is further confirmed by an impulse response function (see Figure 3.1a), in which a shock of one unit of news sentiment on CDS returns (ceteris paribus) in the context of the VAR model is displayed. The effects of this shock are not fully reversed within ten weeks. On the one hand if the news sentiment variable contained only pure information we should not have observed a reversal; on the other hand, if the news sentiment variable contained only pure noise or "sentiment" we should have observed a complete return reversal. The evidence we observe of an initial decline and subsequent partial reversal is consistent with the idea that our news sentiment variable is a mixture of noise and information and that investors over or under-react to this information.

To further investigate the content of the news sentiment variable, we examine the effect of media content on the default and risk premium components. The results are reported in the second and third column of Table 3.6. For the default component, the observed reversal is less pronounced. Only the first two lags are significant and display a negative impact, as significance declines from the 1% for the first lag to 5% at the second lag. This impact is less than is the case for CDS returns, but remains rather large. The F-statistic for the default component returns is 4.17 with a p-value of 0.041, which also allows for a rejection of the null hypothesis of a full reversal. The impulse function shown in Figure 3.1b in this case also confirms the previous result; the effect of a shock of one unit of news sentiment on the default component returns (ceteris paribus) are not fully reversed within ten weeks. Therefore, we conclude that media content contains new information with regard to fundamentals. A different picture emerges for the relationship between media content and the risk premium component (see impulse function for this component in Figure 3.1c). The F-test for the risk premium fails to reject the null of a full reversal. It therefore appears that this component is largely affected by noise implicit in media content. Positive media tone induces optimism and a decline in the risk premium returns followed by a full reversion to initial value. Based on this analysis, we can conclude that the impact of media content on CDS returns- which is accompanied by a partial reversal within five weeks is a mixture of both; new information and noise. However, the noise signal appears to impact the risk premium and leads to a temporary change in investors' appetite for credit exposure. The information signal influences the default risk component and leads to reassessment of the fundamentals of sovereign economies.

Overall our results support a behavioural story. In particular, we can relate the pattern observed in the impulse response function of CDS returns to the theory of over- and underreaction put forth by Daniel, Hirshleifer, and Subrahmanyam (1998). In this setting, investors tend to misinterpret new information. The cognitive psychological investor biases of overconfidence and self-attribution play a key role. These well-documented features of investor psychology are in line with theories of self-deception as in Hirshleifer (2001). Numerous studies have shown that individuals tend to believe that their knowledge is more accurate than it actually is (Daniel, Hirshleifer, and Subrahmanyam, 1998). Overconfidence then spurs over-optimism with regards to the success of a given venture. Naturally then, individuals will experience failure more often than was anticipated, which leads to the emergence of an additional bias: self-attribution. As a result of the said cognitive biases, actors are likely to overweight the accuracy of a private signal they observe. In our context, this may imply that investors are overoptimistic about their ability to interpret the news and believe they may have a better indication of the impact this may have on sovereign's economic fundamentals. This generates an over-reaction to private information. Once said, economic impact becomes clear; the over-reaction is followed by revision of expectations in response to the now public information. This is shown in the "hump shaped" impulse response function. Our findings support those of Hillert, Jacobs, and Müller (2014), which show that media coverage can enhance existing behavioural biases on behalf of investors. These effects are stronger when the tone of news reporting is considered.

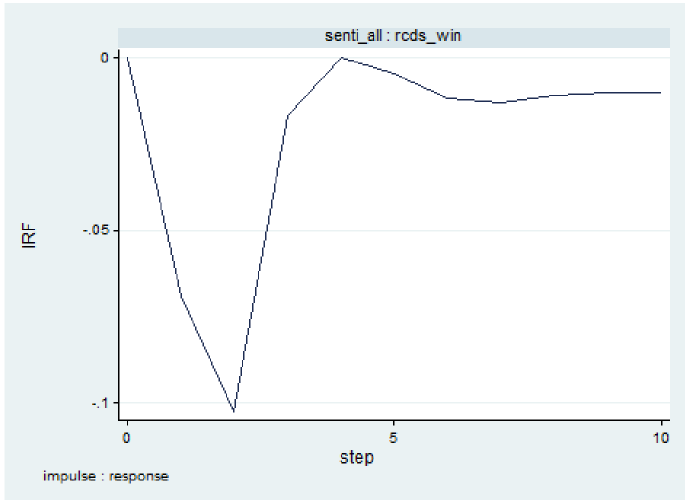
$$News_t = \alpha_i' + \beta_{i,k}' X_{k,t-1} + \sum_{l=1}^{5} \delta_{i,l}' Y_{i,t-l} + \sum_{l=1}^{5} \gamma_{i,l}' News_{t-l} + \epsilon_{i,t}' \tag{3.10}$$

In a second stage, we explore the possibility of a feedback loop between CDS returns and media content. We ask whether a shift in the CDS market induces a change in the tone of news coverage. We run a similar panel VAR, see equation (3.10), by regressing the news sentiment on the five lags of CDS returns and its components. The regressor $Y_{i,t}$ stands for returns of CDS, the default component and risk premium respectively. The results can be found in Table 3.7. As can be seen in the first column, only the second and the fifth lag of our variable of interest, $Y_{i,t}$ (CDS returns), appear to be significant. For the second lag, this relationship is negative while a reversal occurs exclusively in the fifth week, both at the 1% level. Very similar results emerge for the default component shown in the second column pertaining to the regression coefficients. With respect to the risk premium in the final column of Table 3.7, only the third week bears any significance in the VAR regression for our variable of interest and the coefficient is positive. Although not clear cut, it does appear that the main source of causality runs from media content to CDS returns.

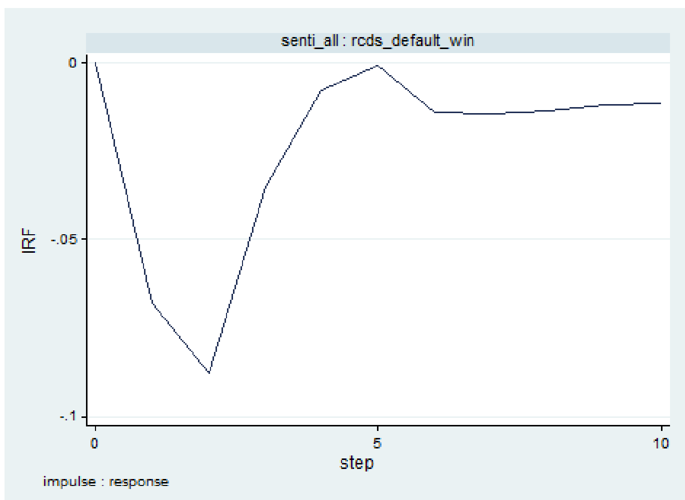
3.6 Conclusion

We explore the interaction between media content and sovereign credit risk. First, we establish whether the linguistic content of news articles can explain and predict sovereign CDS returns. Second, we investigate whether media tone contains hard to quantify aspects of sovereign fundamentals, represents investor sentiment or whether it is a mixture of both. To capture sovereign credit risk, we use an extensive sovereign credit default swap dataset. For media content, we use the sentiment classifications of news from Thomson Reuters News Analytics. We construct a news sentiment variable by filtering news according to global debt markets, US and regional classifiers; Europe, Latin America and Asia. In order to shed more light on the content of media tone, we use an affine sovereign credit risk valuation model to decompose sovereign CDS spreads into their risk-premium and default risk components in line with Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2011). We find that media tone explains CDS and default risk components' returns. The relationship between CDS returns and the news sentiment variable is negative, implying an improvement in media tone (positive) decreases returns. Additionally, using a panel VAR, we show that the news sentiment factor predicts CDS returns, default risk and risk premium components. This result is robust to controls for autocorrelation and determinants of CDS returns. We find that the effect on the CDS and default component returns partially reverses over the following five weeks, whereas the effect on the risk premium reverses fully. This result confirms the hypothesis that media content is a mixture of noise and information. However, the informational channel is more likely to impact the default component whereas the noise channel is more likely to impact the risk premium. Overall, our results support a behavioural story and the theories of over- or underreaction in line with the cognitive biases documented by Daniel, Hirshleifer, and Subrahmanyam (1998).

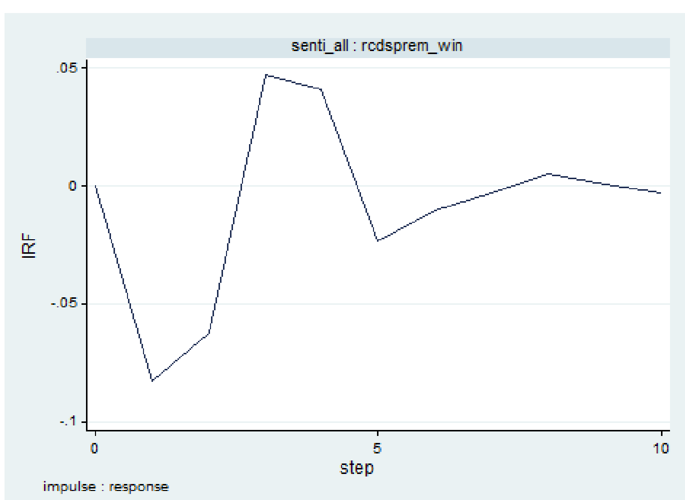
Figure 3.1. Impulse Response Function



(a) CDS returns



(b) Default Component



(c) Risk Premium

Table 3.1. Summary Statistics: CDS Spreads

This table reports the summary statistics for the five-year sovereign CDS contracts for 21 countries. The numbers are reported in basis points. The full sample covers from January 2003 to April 2014. The reported statistics are mean, standard deviation (S.D), minimum (Min), median and maximum (Max).

	Mean	SD	Minimum	Median	Maximum	N
BGARIA	168.63	132.14	12.82	128.91	682.96	569
BRAZIL	273.61	297.12	61.14	150.59	2057.22	569
CHILE	72.73	51.14	12.53	69.45	315.95	569
CHINA	64.12	46.50	9.35	60.64	277.31	569
COLOM	223.68	158.22	67.61	150.81	840.00	569
CROATI	192.89	152.29	15.20	127.50	591.29	569
ISRAEL	97.68	57.94	16.92	103.85	272.86	569
JAPAN	41.17	37.94	2.45	22.31	148.85	569
KOREA	89.42	78.65	14.39	73.14	708.64	569
MALAYS	81.60	57.31	11.96	79.07	505.40	569
MEX	124.01	72.51	28.51	110.44	587.88	569
PANAMA	177.63	102.96	62.15	137.44	590.60	569
PHILIP	246.84	143.33	82.43	187.21	865.63	569
POLAND	89.84	80.71	7.66	68.28	418.56	569
QATAR	75.89	56.07	9.28	66.96	356.20	569
ROMANI	212.44	152.64	16.94	198.45	765.98	569
RUSSIA	185.53	141.44	37.66	158.40	1060.41	569
SLOVAK	70.27	71.71	5.50	54.11	322.03	569
SOAF	139.95	86.57	24.53	136.77	658.08	569
UKRAIN	660.01	703.63	126.62	459.00	5288.98	533
VENZ	825.94	547.66	119.89	770.46	3218.44	569

Table 3.2. Maximum Likelihood Estimates for the Sovereign CDS Parameters

This table reports the maximum likelihood parameter estimates of sovereign CDS for all countries based on the Pan-Singleton Model. The term structure of sovereign CDS considers the three-year, five-year and seven-year CDS contracts for each country. The sample period covers from January 2003 to April 2014 at a weekly frequency.

Country	$\theta^Q\kappa^Q$	κ^Q	σ	$\theta^P\kappa^P$	κ^P
BGARIA	-1.080	0.245	1.734	-1.140	0.456
BRAZIL	3.648	-0.938	0.826	-3.817	0.960
CHILE	-0.477	0.095	1.340	-2.853	0.561
CHINA	-0.456	0.098	1.165	-2.213	0.255
COLOM	3.537	-0.904	0.665	-4.289	1.031
CROATI	-0.539	0.149	1.695	-3.614	0.427
ISRAEL	-1.458	0.306	0.863	-1.736	0.358
JAPAN	-0.604	0.118	0.731	-0.724	0.135
KOREA	-0.552	0.123	1.435	-4.644	0.563
MALAYS	-0.809	0.241	1.081	-1.330	0.275
MEX	-0.624	0.108	2.241	-3.202	0.832
PANAMA	3.899	-0.966	1.261	-4.030	0.978
PHILIP	0.864	-0.029	1.504	-1.612	0.330
POLAND	-0.405	0.051	0.944	-4.776	-0.535
QATAR	-1.469	0.287	0.890	-1.711	0.330
ROMANI	-4.636	1.167	2.570	-4.818	1.199
RUSSIA	-1.610	0.202	1.617	-1.772	0.109
SLOVAK	-0.194	0.048	1.043	-1.430	0.269
SOAF	-0.564	0.096	1.843	-2.514	0.594
UKRAIN	-11.143	4.112	5.051	-10.968	4.028
VENZ	-0.784	0.309	0.646	-0.794	0.309

Table 3.3. Summary Statistics: Credit Risk Premium

This table reports the summary statistics for sovereign credit risk premium for 21 countries. Number reported in in basis points. The full sample covers from January 2003 to April 2014. The reported statistics are mean, standard deviation (S.D), minimum (Min), median and maximum (Max).

	Mean	SD	Minimum	Median	Maximum	N
BGARIA	27.53	18.82	-17.10	22.99	74.57	569
BRAZIL	57.61	37.09	-53.11	39.93	253.61	569
CHILE	20.18	12.62	-0.10	20.60	63.96	569
CHINA	19.40	13.23	3.06	15.96	55.30	569
COLOM	57.20	32.63	19.72	40.14	151.15	569
CROATI	25.66	18.11	-11.95	19.78	65.62	569
ISRAEL	23.80	12.55	3.74	24.07	55.37	569
JAPAN	14.22	13.24	0.72	7.76	43.23	569
KOREA	18.61	11.97	-0.53	15.32	53.74	569
MALAYS	22.51	13.39	4.08	21.41	55.34	569
MEX	32.61	12.28	7.20	32.72	73.21	569
PANAMA	48.85	24.69	19.84	37.05	131.80	569
PHILIP	63.39	30.57	-3.39	52.56	177.59	569
POLAND	19.23	14.15	0.38	15.64	54.47	569
QATAR	18.50	10.60	2.68	15.50	44.59	569
ROMANI	31.64	23.75	-28.77	24.91	93.48	569
RUSSIA	28.82	29.69	-144.10	28.38	94.20	569
SLOVAK	15.71	14.47	-3.13	12.37	53.26	569
SOAF	30.75	13.77	0.34	31.18	57.01	569
UKRAIN	91.44	349.37	-297.77	49.01	3485.93	533
VENZ	74.86	151.11	-141.13	62.33	1409.82	569

Table 3.4. Principal Components Analysis

This table reports the summary statistics for the principal components analysis and the correlation analysis from January 2003 to April 2014. The PCA analysis is reported on the left side of the table based on the correlation matrix of weekly returns for sovereign CDS, default components and risk premium. The right side of the table reports the correlation analysis between the first three principal components and three potential risk factors. ***stands for 1% significant level.

Principal Components Analysis			**Correlation between PCs and Risk Factors**			
	CDS Returns				**CDS Returns**	
Component	**Proportion**	**Cumulative**		**News**	**VIX Risk**	**US Stock**
First	0.6238	0.6238	**First**	-0.1523***	-0.2957***	-0.1504***
Second	0.0609	0.6847	**Second**	0.0384	-0.0989	-0.012
Third	0.051	0.7357	**Third**	-0.0157	-0.0721	0.061
	Default Component				**Default Component**	
Component	**Proportion**	**Cumulative**		**News**	**VIX Risk**	**US Stock**
First	0.5719	0.5719	**First**	-0.1514***	-0.2843***	-0.1449***
Second	0.0614	0.6333	**Second**	0.0523	-0.0816	0.0182
Third	0.0519	0.6852	**Third**	-0.0083	-0.0503	0.061
	Risk Premium				**Risk Premium**	
Component	**Proportion**	**Cumulative**		**News**	**VIX Risk**	**US Stock**
First	0.1407	0.1407	**First**	-0.1213***	-0.1796***	-0.1407***
Second	0.0724	0.2131	**Second**	0.1085	-0.1914***	0.0607
Third	0.065	0.2781	**Third**	-0.012	0.0661	-0.0299

Table 3.5. Panel OLS Regression

The following table reports the panel regressions of the three components: sovereign CDS returns, the default component and the risk premium. Explanatory variables include global risk factors, local variables, sovereign spreads as well as news sentiment. The sample period is from January 2003 to April 2014. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	CDS Return	**Default Component**	**Risk Premium**
Global risk factors			
US stock market	-0.005***	-0.006***	0.002
Volatility premium	-0.003***	-0.003***	-0.001**
Term premium	0.001***	0.001	0.002***
Treasury market	0.122***	0.133***	0.043***
Investment grade	-0.003***	-0.004***	0.002
High yield	1.294***	1.554***	0.283***
Local variables			
Exchange return	-0.079	-0.078	-0.175
Stock return	-0.176***	-0.202***	0.045
Sovereign spreads			
Regional spread	0.205***	0.218***	0.020
Global spread	0.663***	0.764***	0.227***
News sentiment	-0.122***	-0.137***	-0.025
Constant	0.000	0.002*	-0.001
N	10,775	10,775	10,775
Adjusted R^2	0.663	0.598	0.018

Table 3.6. VAR Regression Using News Sentiment

The following table reports the panel VAR regression based on weekly returns of sovereign CDS spreads, default risk and risk premium for five lags of news sentiment, five lags of the return components itself (not reported in the table), in addition to robust explanatory variables including global risk factors, local variables and sovereign spreads. The sample period is from January 2003 to April 2014. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	CDS Return	**Default Component**	**Risk Premium**
Global risk factors			
US stock market (t-1)	-0.014***	-0.017***	-0.005**
Volatility premium (t-1)	0.002***	0.002***	-0.000
Term premium (t-1)	-0.001***	-0.001	-0.001
Treasury market (t-1)	-0.033***	-0.027**	-0.015
Investment grade (t-1)	0.001	0.001	0.000
High yield (t-1)	0.079	0.179***	-0.056
Local variables			
Exchange premium (t-1)	-0.113	-0.178*	0.079
Equity premium (t-1)	-0.062	-0.094**	0.050
Sovereign spreads			
Regional spread (t-1)	0.016	0.030	-0.012
Global spread (t-1)	0.014	0.040	0.037
News sentiment (t-1)	-0.069***	-0.068***	-0.083**
News sentiment (t-2)	-0.071***	-0.060**	-0.029
News sentiment (t-3)	0.052**	0.024	0.092**
News sentiment (t-4)	0.044**	0.041	0.045
News sentiment (t-5)	0.010	0.023	-0.033
Chi2 (5) [Joint]	54.139***	33.834***	13.323**
N	11,766	10,673	10,673

Table 3.7. VAR Regression for Feedback Reaction

The following table reports the panel VAR regression of news sentiment on five lags of different CDS components, five lags of news sentiment (not reported in the table), as well as robust explanatory variables including global risk factors, local variables and sovereign spreads. The sample period is from January 2003 to April 2014. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	CDS Return	**Default Component**	**Risk Premium**
Global risk factors			
US stock market (t-1)	0.007***	0.007***	0.007***
Volatility premium (t-1)	-0.001***	-0.001***	-0.001***
Term premium (t-1)	0.001***	0.001***	0.001***
Treasury market (t-1)	-0.026***	-0.025***	-0.026***
Investment grade (t-1)	0.000**	0.000**	0.000***
High yield (t-1)	-0.031	-0.026	-0.050***
Local variables			
Exchange premium (t-1)	-0.014	-0.016	-0.018
Equity premium (t-1)	0.013	0.012	0.014
Sovereign spreads			
Regional spread (t-1)	0.010	0.011	0.011
Global spread (t-1)	-0.011	-0.008	-0.013
Y (t-1)	-0.008	-0.010	-0.000
Y (t-2)	-0.021***	-0.015***	-0.001
Y (t-3)	-0.004	-0.005	0.007***
Y (t-4)	0.001	0.001	0.001
Y (t-5)	0.024***	0.021***	0.001
Chi2 (5) [Joint]	50.378***	51.368***	8.078
N	11,766	10,673	10,673

Chapter 4

The Impacts of News and Investor Attention in the Credit Default Swap and Equity Markets

4.1 Introduction

Several studies have demonstrated that sentiment analysis has wide implications for understanding the nature of financial transactions, volumes and price movements, and predicting future returns (Tetlock, 2007; Jegadeesh and Wu, 2013; Garcia, 2013; Cathcart, Gotthelf, Uhl, and Shi, 2016; Loughran and McDonald, 2011). In the previous chapter, we study the relationship between media content and sovereign credit risk. The results suggest that media content contains new information about sovereign fundamentals, and has a significant impact on the sovereign CDS returns. In this chapter, we aim to extend the empirical framework to explore the relationship between the media content and corporate credit risk. To do so, we construct a sentiment score variable by using the 'bag-of-words' linguist textual analysis algorithm (Loughran and McDonald, 2011; Liebmann, Orlov, and Neumann, 2016). For companies, we focus on the most liquid U.S. financial firms in the S&P 500 financial sector index. We collect the news articles of each firm from the Wall Street Journal (WSJ). The choice of the WSJ is simply because it is a New York City based mainstream business-oriented newspaper, which is published by the Dow Jones & Company. Furthermore, it is the journal that is used in various studies, such as Tetlock (2007); Tetlock, Saar-Tsechansky, and Macskassy (2008); Dougal, Engelberg, Garcia, and Christopher (2012).

To measure the corporate credit risk, we use the single-name CDS contract. There is no doubt that CDSs remain controversial financial products, especially in the light of the financial crisis 2007/08 and the European sovereign crisis. In particular, CDSs were blamed for facilitating speculation on potential government defaults, which artificially drove up the borrowing cost for major sovereigns. In November 2012, the European Commission issued a ban that forbids investors to short sell 'naked' sovereign CDS, which illustrates the concern of commentators and regulators about the use of CDS contracts to exploit private information for excessive profits and potential price manipulations. Hence, it is reasonable to ask the question whether the CDS market really influences prices changes in other markets. Standard financial theory suggests that in a perfectly efficient financial market, all derivatives based on the same underlying assets are exposed to the same fundamental risks. Therefore, any new information about the underlying assets would be reflected in all relevant markets. In practice, due to reasons such as regulations, trading conventions, leverage constraints and transaction costs, it is often that specific investors have particular preferences for certain types of securities. Various studies have highlighted the potential price discovery dynamics among different markets, such as stock, bond and CDS markets (e.g., Norden and Weber, 2004; Forte and Peña, 2009; Acharya and Johnson, 2007, 2010).

We'd like to address the above issue via a different angle. We investigate the reactions of different assets to the same news sentiment. Specifically, we focus on the CDS and equity markets. Important corporate news influences capital markets across different asset classes. The literature of price discovery suggests that equity returns tend to the primary market where new information is discovered, in comparison to the CDS and bond markets (e.g., Marsh and Wagner, 2012; Norden and Weber, 2009, 2004; Forte and Peña, 2009; Hilscher, Pollet, and Wilson, 2015). We follow the same logic and propose the following hypothesis. If the price discovery process is led by the equity market and lagged in the CDS market, we would observe a faster response to news sentiment in a firm's equity return than its credit return. We find significant price reactions in the equity market on the day of news release. Furthermore, the impact of news on the equity returns reverses within two days. However, CDS returns illustrate a significant delay in responding to the news. The CDS spread reactions do not occur until the second day. It takes another two to three days for the CDS returns to absorb the information and fully reverse. Robustness checks confirm that the superior reactions to news illustrated by equity returns over the CDS returns are consistent over different regression settings, and are unaltered when we separate the sample into crisis and non-crisis periods. One possible explanation is the inattention of CDS traders. Studies have shown that human attention is a scare resource. Furthermore, limits of human attention affect market prices (DellaVigna and Pollet, 2007; Barber and Odean, 2008; Cohen and Frazzini, 2008; Mamaysky and Glasserman, 2016). The study by Hilscher, Pollet, and Wilson (2015) suggests that informed traders prefer to trade in the equity market, while CDS traders are uninformed traders with liquidity preferences.[1] Since the CDS traders are predominantly trading for nonfundamentals-based reasons, they may not be as attentive to the news development as equity market traders. This helps to explain the slower response to news sentiment for CDS returns.

Our second finding is directly linked to Garcia (2013). We find the impact of news sentiment on the CDS and equity returns increases substantially during the crisis period, in comparison to the non-crisis period. Furthermore, we compare the news reaction patterns of CDS returns for the crisis versus non-crisis periods. We observe a significant improvement in the impact of media sentiment on the credit returns during the crisis period, statistically and economically. In addition, the results show that during the crisis period, liquidity risk factor becomes significant in explaining CDS returns, which is not the case during the non-crisis period. The simultaneous improvements in the impacts of the news content and the liquidity risk on the CDS returns provide evidence to a

[1]The specific liquidity preferences and the underlying reasons are assumed to be exogenous in the original theoretical model of Easley, O'hara, and Srinivas (1998).

separate equilibrium market setting, which is proposed by Easley, O'hara, and Srinivas (1998). In their model, there are two types of investors: the informed traders, who decide to trade either in the equity or the option market, and the uninformed liquidity traders.[2] The presence of the latter would allow the informed traders to benefit from their superior private information without exposing their identities. In this setting, the informed trader can either choose to 'pool' and trade in both markets, or to 'separate' and trade in only one market. The choice of the informed traders on which market to trade depends on whether the market 1) is highly sensitive to information 2) has low transaction costs and 3) has a large proportion of uninformed traders. Hilscher, Pollet, and Wilson (2015) show that high bid-ask spreads of the CDS market deter informed traders from joining the credit market in despite of a large fraction of uninformed traders in the CDS market and high sensitivity of the credit securities to new information. The informed traders opt for the equity market due to its low bid-ask spreads and large transaction volume, whereas the CDS market is filled with uninformed traders who have liquidity preferences. The authors also find that the credit protection returns respond more quickly during salient news events such as corporate earnings announcement, which presumably both CDS and equity traders are more likely to pay attention to (Greatrex, 2009; Frazzini and Lamont, 2007). Therefore, we argue, during the financial crisis, the rises of liquidity and funding risks force the uninformed liquidity traders to carefully monitor the market liquidity condition, resulting in increasing attentions to market news from the CDS traders and improved news reactions.

The remainder of this chapter is organised as follows: section 4.2 reviews the existing literature on sentiment analysis, price discovery and investor inattention theory. Section 4.3 provides a detailed description of the data and variables used in this study, with a specific focus on the news sentiment score construction. The empirical investigations and findings are discussed in section 4.5. Section 4.6 concludes.

4.2 Literature Review

Our work is related to various strands of the literature. Firstly, it is related to studies that investigate the impact of news sentiment on asset market performance. Tetlock (2007) documents the evidence that news media content can predict movements in broad indicators of stock market activity. The author uses a quantitative content analysis programme to study the daily variation in the WSJ 'Abreast of the Market' columns from 1984 to 1999, and to construct a simple measure of media pessimism.[3] Tetlock, Saar-Tsechansky, and Macskassy (2008) explore the same research question but focus on the predictability of negative words. Their findings suggest that linguistic media content captures otherwise hard-to-qualify aspects of firms' fundamental, which would be incorporated quickly into the stock prices. Garcia (2013) shows that the predictability of stock returns using news content is concentrated in recessions. Furthermore, the study by Dougal, Engelberg,

[2] The option market extends for any alternative derivative market.

[3] The content analysis programme used is the General Inquirer.

Garcia, and Christopher (2012) distinguishes a reflective and a causal role of financial media by using the exogenous rotation scheduling of the WSJ columnists. They find that financial reporting has a causal impact on the stock market performance. Engelberg and Parsons (2011) disentangle the causal impact of the content of media reporting from the impact of the event. The authors use 19 mutually exclusive trading regions in U.S. and study the reactions of local investors to the same information event. They find that local media coverage strongly predicts local trading, and that local trading is strongly related to the timing of local reporting. A rather ambitious study is conducted by Hillert, Jacobs, and Müller (2014). The paper uses 2.2 million articles from 45 national and local U.S. newspapers between 1989 and 2010 to study the impact of media coverage on cumulative stock returns. They find that firms particularly covered by media exhibit stronger momentum and that this effect depends on media tone. Intensive media coverage exacerbates investor biases. Unlike traditional studies that focus on stock returns, Mamaysky and Glasserman (2016) study the impact of news unusualness on predicting realised and implied volatilities of individual stocks and the aggregate market.

More recent studies explore the impact of news sentiment on the price of credit products. Tang and Yan (2010) find that investor sentiment is the most important determinant of credit spreads. The study by Tang and Yan (2013) uses the VIX index as a measure of market 'fear' sentiment and finds it significantly explains changes in CDS spreads. Cathcart, Gotthelf, Uhl, and Shi (2016) use advanced news sentiment sequences from Reuters and find that media content significantly impacts the sovereign CDS movements, as well as the expected default component. It is worth mentioning that our work is closely linked to the study by Liebmann, Orlov, and Neumann (2016). We both use sophisticated linguist content analysis programmes to build a news sentiment measure, and study its impact on the CDS and equity returns. However, our focus is rather different. Their purpose is to study how traders of different markets interpret and react to the same news texts. In particular, two filtered news series are constructed: the corporate event news and the debt news. Our focus is on the speed and magnitude of the news reaction process in each market, and on any differences in the patterns between the two markets. In particular, we study the causal relationship between news sentiment and the stock returns (and between news sentiment and CDS returns). We document a delayed response of the credit market to news sentiment, in comparison to the equity market.

Secondly, we contribute to the literation that studies the price discovery process between the CDS market and equity market. Acharya and Johnson (2007, 2010) show that insider trading activity occurs in the CDS market. Such private information is then slowly incorporated into the stock price. On the other hand, various studies suggest the opposite lead-lag relationship. That is, the stock market leads the CDS market in exploring new information about market condition and firm fundamentals. Forte and Peña (2009) study the price discovery across stock, CDS and bond markets with a sample of 17 North American and European non-financial firms from 2001 to 2013. Norden and Weber (2009) extend the same empirical framework to a lager cross-sectional data set, which contains 58 firms from 2000 to 2002. Both studies draw the same conclusion that the stock market leads the CDS market and the bond market in price discovery. Daily lead-lag relationship between the CDS and equity markets is studied by Marsh and Wagner (2012). The paper of Hilscher, Pollet, and Wilson (2015) find that equity returns lead credit protection returns at daily and weekly frequencies, whereas credit protection returns do not lead equity returns. Our study provides aligned evidence that the equity market illustrates a more rapid response to news sentiment, in comparison to the CDS market.

Thirdly, we link our findings to the investor inattention theory (Easley, O'hara, and Srinivas, 1998; DellaVigna and Pollet, 2007, 2009; Cohen and Frazzini, 2008; Barber and Odean, 2008). The theory claims that limits of human attention affect market prices. For example, DellaVigna and Pollet (2007) show that investors are inattentive to information with long-term consequences. DellaVigna and Pollet (2009) find that reduced investor attention causes less immediate responses to earnings announcements on Friday. An interesting study by Ehrmann and Jansen (2012) finds that traders were distracted during the World Cup matches in 2010. When the national teams were playing, the trading volumes of the corresponding countries' stock markets dropped substantially. Hirshleifer, Hou, Teoh, and Zhang (2004) construct an accounting measure, the cumulative difference between operating income and free cash flow, which quantitatively captures the investors' inattention. This measure is based on the assumption that investors with limited attention tend to neglect information about cash profitability, and focus on accounting profitability. They find that this inattention measure significantly predicts long-run stock returns. The study by Mamaysky and Glasserman (2016) suggests that inattentive investors pay less attention to the short-term volatility, but focus more on the long-term market pressure. Hilscher, Pollet, and Wilson (2015) find that CDS traders are liquidity traders and are inattentive to news development, in comparison to the informed traders in the equity market. Furthermore, they find credit traders respond more quickly during the salient news events, such as earnings announcements (Frazzini and Lamont, 2007; Greatrex, 2009). A similar finding is also documented in Norden and Weber (2004) that the CDS spreads react faster than the equity returns only during negative rating announcements. Our findings provide evidence that supports the investor inattention explanation. As suggested by Easley, O'hara, and Srinivas (1998); Hilscher, Pollet, and Wilson (2015), CDS traders have preferences for liquidity and pay less attention to news about fundamentals, leading to a delay in the response of credit returns to the news sentiment. Furthermore, we find credit returns react faster during the crisis period than the non-crisis period. Simultaneously, the explanatory power of the liquidity risk becomes significant during the crisis period. The Great Recession was highlighted as a liquidity-induced crisis; higher liquidity risk forces CDS traders to pay more attention to relevant market news, which causes a more rapid reaction of CDS returns during this period.

4.3 News, Data and Other Variables

This section starts with a description of the filtration steps on the financial firms selection. It is followed by a detailed elaboration of the news articles collection process, as well as the news sentiment score construction. In the end, we summarise the relevant information on the CDS data, equity price, and other explanatory variables.

4.3.1 The Financial Firms

First, we download the constituent name list of the S&P 500 financial sector index. We use the list which was published by the S&P Dow Jones Indices in February 2016.[4] The full name list contains 90 financial firms. Second, we cross check the firm names against the Markit CDS reference entity name list. We filter out firms that have not underwritten any CDS contract. The updated name list contains 64 firms. We use news articles published by the Wall Street Journal. The total number of news observations on an individual firm is rather limited, especially during the period 2001-2003. Therefore, in the third step, we exclude firms which have less than 100 relevant news articles over the sample period.[5] After these steps, 31 U.S. financial firms are selected for the empirical study.[6] Table 4.1 lists the companies used in our sample.

4.3.2 The News

Our data set of news consists of Wall Street Journal news articles about the 31 S&P 500 financial firms. The news articles are extracted from Factiva. The only additional search criterion we used is the language as English. We then set the company criteria as the subjective firm name, and download all articles in the displayed search results for each firm in the list. The raw data contains over 28,000 news articles from January 2001 to June 2016. Various reports occur multiple times for reasons such as rewriting of the same original story, or repeated releases in different versions of the journal (i.e., the WSJ U.S. versus the WSJ Europe). For these cases, we keep the first presence of such article in data set. This leaves us with 15,827 news articles which we use to construct the news score. There are many articles that mention more than one firm. This distinguish our study from Liebmann, Orlov, and Neumann (2016) as our news sample contains all relevant news of a company as long as its name is shown or tagged in the article, whereas their paper focuses on two specific categories of news articles: the corporate event news and the debt news.

For each news article we collected, we perform linguist textual analysis. We analyse the text content of each news release in order to determine its sentiment direction. In particular, the analysis

[4] http://us.spindices.com/indices/equity/sp-500.

[5] The third step of firms filtration would not be necessary once we enrich the news articles entries. We plan to include news articles from Reuters, Bloomberg and Financial Times etc.

[6] The majority of our firms also are the constituents for the CDX.NA.IG index.

we conduct is the traditional sentiment evaluation process, which calculates the fraction of words in a given article that have negative or positive connotations (Mamaysky and Glasserman, 2016; Loughran and McDonald, 2011; Jegadeesh and Wu, 2013). This score-based algorithm is also known as the "bag-of-words" approach and requires word dictionaries and corpus. The Harvard IV-4 psychosocial dictionary is used in the studies such as Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008). The recent work by Loughran and McDonald (2011) creates the Laughran-McDonald word list, which is based on sophisticated analyses on the 10-K SEC filing documents of the U.S. corporations.[7] Research by (Loughran and McDonald, 2011; Heston and Sinha, 2014; Sinha, 2016) show such word list has a superior accuracy for sentiment analysis in the financial field than the Harvard dictionary. For this reason, we use the Laughran-McDonald word list. Furthermore, we extend our dictionary with the MPQA Lexicons, including the Opinion and Emotional-based Subjectivity Sense Annotations lexicon and the GoodFor/BadFor Corpus.[8] For each news article, the algorithm produces a sentiment score. A positive score indicates investors are optimistic about the future market growth, while a negative score suggests investors are pessimistic about the market movement. Sometimes, multiple news reports may occur in one day. For each company and for each day, we calculate the average scores over all articles which are published on that day. Once the series of the news score is constructed, we standardise it at firm level. The corresponding score is the ultimate sentiment news variable used in the empirical regression.

4.3.3 The CDS and Equity Data

We use the single-name CDS contract as a proxy for firm-specific credit risk. We prefer CDS spreads to corporate bond yields for several reasons. Firstly, the CDS contract is typically traded on standardised terms, and its spread provides a relatively pure measure of the default risk of the underlying entity. This is because bond yields are very sensitive to contract specifications such as coupon rate, debt seniority, embedded option, convention and corporate guarantees (Zhang, Zhou, and Zhu, 2009). Studies by Longstaff, Mithal, and Neis (2005) and Chen, Lesmond, and Wei (2007) suggest that a large proportion of cross-sectional variations in corporate bond yields are linked to the market liquidity risk, instead of specific firm default risk. Secondly, Marsh and Wagner (2012) and Zhu (2006) find that the CDS market leads the bond market in price discovery, especially for the information that reflects changes in credit conditions.

We download the corresponding CDS spreads of the 31 firms we selected from Markit. The sample period ranges from 3rd January, 2001 to 14th June, 2016. We choose single-name CDS contracts with five-year maturity, because they are the most traded and most liquid maturity in the CDS term structure. Furthermore, we include the CDS observations that are underwritten on senior debt issued by these firms. It is because the market for CDS contracts written on senior debt is more

[7] The list is downloaded from http://www3.nd.edu/ mcdonald/Word_Lists.html.

[8] MPQA resource is sponsored by the University of Pittsburgh on annotated corpus, subjectivity lexicon, political debate data: http://mpqa.cs.pitt.edu/.

liquid than the market for subordinate bonds.[9] Furthermore, the recovery criteria on the underlying bond is set as 'Modified Restructuring', since such default definition clause is the most common restructuring convention used for U.S. firms (Hilscher, Pollet, and Wilson, 2015; O'Kane, 2011b). The notional of all CDS contracts is expressed in US dollars. For any missing data points, we bootstrap the data by using the credit term structure, including CDS contracts with maturity of one, two, three, five, seven, and ten year. The summary statistics for the five year CDS spreads on the 31 firms are reported in Table 4.2.[10]

For the dependent variables, we use CDS protection return (phrases such as credit return or CDS return are used interchangeably) and equity return on each firm. The CDS protection return is used in the studies of Hilscher, Pollet, and Wilson (2015); Cathcart, Gotthelf, Uhl, and Shi (2016). Since the release of the CDS Big Bang on 8th April, 2009, the trading convention for CDS contracts has been changed. Originally, the single-name corporate CDS contract was quoted in its par spread, which sets the discounted present value of a CDS contract to be zero for both protection buyer and seller at the outset of the trade (it is the standard CDS spread definition in a CDS pricing model).[11] The new protocol standardises the single-name CDS trading with a fixed coupon, which is 100 basis points or 500 basis points, plus an upfront fee. The upfront fee would be equal to the discounted present value of the CDS, which compensates the difference between the fixed coupon and the actual premium for the trade. Consider an investor purchases a CDS contract at time t with upfront points of s_t and at time $t+1$, the investor sells an offsetting CDS contract with upfront points of s_{t+1}. The cash flow associated with such a trade would be $s_{t+1} - s_t$. Hence the expected return of the investor at time t is $r_{t,cds} = \frac{s_{t+1} * D^{1/360} - s_t}{s_t}$, where D is the annuity discount factor. Since we are using daily observations, this annuity factor is always close to 1. Therefore, we calculate the percentage changes in the credit spread as the CDS return in the empirical analysis.

The equity return of each firm is the percentage changes of its closing stock price. The data is extracted from Bloomberg. Furthermore, all returns data (both the CDS and the equity returns) are winsorised at the 1% and the 99% levels. That is, extreme outliers which exceed the cut-off points are replaced with the observation value in the 1st and 99th percentile.

4.3.4 Explanatory Variables

For control purpose, we also include a list of explanatory variables to capture global, financial and firm-specific risk factors. Three macro-economic and financial variables are used to capture the overall condition of the economy and the financial market. The 'US stock market' variable is the

[9] Senior debt entitles the bond holder to seniority (over subordinate debt) when claiming losses, given that the bond issuer defaults on both senior and subordinate bonds. Senior debt contains less credit risk and has a better recovery rate.

[10] It is based on raw observations downloaded from Markit.

[11] See: http://www.isda.org/bigbangprot/bbprot_faq.html#cdi14.

daily excess return of the S&P 500 index. The 'volatility premium' is the difference between CBOE VIX index and the realised 30-day volatility of the S&P 500 stock index. We also consider the market 'liquidity risk' because the CDS market demands a mark-to-market margin system and requires investors to post collaterals. The liquidity risk is calculated as the difference between 3-month Libor rate and the USD OIS rate. The standard Merton (1974) default risk framework builds a direct link between a firm's default risk and the volatility of such firm's asset value. We use the past 30-day realised volatility of the firm's equity return as a firm-specific risk factor. We also construct other standard structural factors, such as dividends payout ratio and leverage ratio (Zhang, Zhou, and Zhu, 2009). In addition, we construct two corporate credit market variables, the investment grade spread and the high yield spread. Interestingly, we find these two factors are highly correlated with the realised volatilities of individual firms. Therefore, we do not include these two variables in our empirical framework.[12] All aforementioned data are extracted from Bloomberg.

4.4 Pooled Vector Autoregression

Before moving to the formal regression analyses, we perform a preliminary test on the cross-predictability between the CDS and equity returns as in Hilscher, Pollet, and Wilson (2015). We adopt the same econometric tool, the simplest pooled vector autoregression (VAR). Besides running pooled VAR on the full sample period, we also run it on two sub-sample periods. That is, the exact same period as in Hilscher, Pollet, and Wilson (2015) from 2001 to 2007, and the crisis period from 2008 to 2009.[13] The coefficient statistics for the full sample period regression are reported in Table 4.3, and the results for the two sub-sample periods are reported in Table 4.4. The t-statistics are based on standard errors that are clustered by firm id, and are adjusted for heteroskedasticity.

The study of Hilscher, Pollet, and Wilson (2015) finds that equity returns can significantly predict the credit protection returns, but not vice versa. Furthermore, in comparison to the autoregressive credit protection return itself, the equity returns show a superior forecasting power to the credit returns. Our findings of the sub-sample period from 2001 to 2007 are aligned with these discoveries. The top panel of Table 4.4 shows that the one-day lagged equity returns can significantly predict the CDS returns at the time t, whose statistical significances are much stronger than the lagged CDS returns. On the other hand, the one-day lagged credit returns have no forecasting power on the equity returns. This suggests that the informed trading occurs in the equity market first.

However, the findings from the crisis period (as well as the full-sample period) show a different story. As shown in the lower panel of Table 4.4, we observe enhanced statistical significance illustrated

[12]The correlations are as high as 97 percent on levels, and 11 percent on changes. The correlations are significant at 0.00001 percent level.

[13]The pooled VAR is also performed on the entire no-crisis period, the regression results stay consistent as the results shown in the sum-sample 2001-2007.

by the autoregressive CDS returns in predicting the credit returns. Furthermore, the lagged credit returns also significantly forecast the movements in the equity returns at time t. These findings suggest, during the financial crisis period, the equity returns predict credit protection returns, and vice versa. It is, therefore, hard to determine the direction of information flow, neither the location of informed traders. These preliminary tests document similar behaviour patterns to the one reported in the existing literature but also highlight new results pertaining to the crisis period.

4.5 Regression Analyses

As the purpose of this study is to examine and compare price reactions to news media content of the equity and CDS markets, it is essential to establish the explanatory power of our news score variable. We perform simple OLS panel regressions of the equity and CDS returns on the news score. In addition, we separate our sample into crisis and non-crisis periods. The crisis period is the U.S. financial crisis from January 2008 to December 2009. We also investigate the interaction between the CDS (equity) return and the news media content via a panel vector autoregressions (Panel VARs) and the corresponding impulse response functions.

4.5.1 Panel Regression

We perform panel regression as shown in equation (4.1) across the 31 financial firms. $Y_{i,t}^{k}$ stands for the CDS protection return, and the equity stock return, respectively. We control for heteroskedasticity by clustering the standard error at firm level. A firm specific fixed effect is included to control for unobserved average cross-sectional differences. We also include a year effect to capture the influence of aggregate time-series trends in the sample. We ensure all variables are stationary at the panel setting. The regression is performed on the daily observations of the CDS protection return and the equity return.

$$\begin{aligned} Y_{i,t}^{k} \quad = \quad & \alpha_i^k + \beta_{i,1}^k NewsScore_{i,t} + \beta_{i,2}^k Volatility\ premium_t \\ & + \beta_{i,3}^k Equity\ volatility_{i,t} + \beta_{i,4}^k US\ stock_t \\ & + \beta_{i,5}^k Liquidity\ risk_t + \epsilon_{i,t}^k \\ & k \in \text{CDS return},\ \text{equity return}; \quad \forall i \in 1, ..., 31; \end{aligned} \tag{4.1}$$

The regression results of equation (4.1) are reported in Table 4.5. Columns 1, 3 and 5 report the coefficient statistics of the explanatory variables for the CDS returns. Columns 2, 4 and 6 are the regression coefficients for the equity returns. Columns 1 and 2 are based on the full sample observations. Columns 3 and 4 are based on the observations of the U.S. financial crisis, and columns 5 and 6 report the results for the non-crisis period. The adjusted R-squared and the number of observations are also reported in the table. The t-statistics are in the parentheses.

There are several interesting findings that emerge from the panel regressions. Firstly, the news score variable has a significant impact on the equity returns for the entire sample regression, as well as the ones for the sub-sample periods. However, the news media content only impacted the CDS returns significantly during the Great Recession. Secondly, focusing on the crisis period, the news score has a negative impact on the CDS returns, while a positive impact on the equity returns. One standard deviation increase in the news score decreases CDS returns by 16.5 percent while increases equity returns by 31.5 percent. This finding is in line with the existing literature that positive news depresses credit returns but improves equity returns (Liebmann, Orlov, and Neumann, 2016). It also confirms the negative relationship between the CDS and the equity returns (Zhang, Zhou, and Zhu, 2009; Cremers, Driessen, Maenhout, and Weinbaum, 2008). Thirdly, comparing the coefficients of the news sentiment on the equity returns across the two different sub-samples, we observe substantial increases in the magnitude and the significance level of the coefficient, from 0.036 at a significance level of 5 percent of the non-crisis period, to 0.315 at a significance level of 1 percent of the crisis period. The coefficient of the non-crisis period is consistent with the result based on the full sample observations. Such improvement in the magnitude and statistical importance of the news media score confirms the findings in Garcia (2013): the impact of news sentiment tends to concentrate during recessions. The same logic also applies to the CDS returns. During non-crisis period, the news score is insignificant and with inappropriate sign (and the full sample period). During the crisis period, the news sentiment suddenly becomes significant at 5 percent level and with the correct sign.

Hilscher, Pollet, and Wilson (2015) suggest the inattention theory would help to explain the changing responses of credit returns to the news. The theory suggests that CDS traders are less attentive than equity traders to events of common concerns because CDS traders are motivated by liquidity considerations. Therefore, we do not observe a significant impact of the news on credit returns during the non-crisis period. However, during the crisis period, both liquidity and funding risks increase. Risk-averse CDS traders need to pay more attention to the market sentiment in order to gather information on market liquidity conditions. This explains the significance of news score variable on CDS returns during the crisis period. This explanation could be further supported by the coefficients of the liquidity risk across different samples. There is no significant impact of liquidity risk on the CDS returns before or after the financial crisis. However, during the financial crisis, the liquidity risk factor starts to impact CDS returns significantly. One basis point relative increase in the 3 month Libor rate over the OIS rate increases CDS returns by 8.9 percentage points, at 1 percent significance level. This increasing explanatory power of the liquidity risk factor, presumably, suggests an increase of the attention from CDS traders on the market liquidity condition during the Great Recession. With respect to the other control variables, the U.S. equity market return remains the most important global risk factor (Longstaff, Mithal, and Neis, 2005; Longstaff, Pan, Pedersen, and Singleton, 2011), which significantly impacts both CDS and equity returns, in the full period and both sub-sample periods. One percentage increase in the U.S. stock market return decreases

CDS returns by 4.81 (column 1) percentage points, while increase equity returns by 134.1 (column 2) percentage points. The realised volatility of a firm's equity return has a significant impact on the CDS returns in the non-crisis (and full period) sample. A higher volatility of the stock price implies a higher risk of the CDS's underlying firm, and hence a higher CDS spread. The insignificant impact of the equity volatility on the firm's equity return can be explained by the inclusion of the firm fixed effect.[14] The volatility premium of the U.S. VIX index has explanatory powers on both return series, but for different sample periods. The volatility premium significantly impacts CDS returns during the non-crisis period, while critically influences equity returns in the crisis period.

Regarding the explanatory power of the overall model, the adjust R-squared for CDS returns is not as promising as for equity returns. For the entire sample, our model explains 3.5 percent variations in the cross-sectional CDS returns, but 42.6 percent variations in the equity returns. The low adjusted R-squared for CDS returns could be caused by the lack of debt level information, such as leverage and other balance sheet factors. Indeed, we observe a higher adjusted R-squared for CDS returns when we include the balance sheet variables such as leverage ratio, dividend payout ratio, return on equity, etc. Inclusion of these variables does not change our findings on the news score. Due to the different frequency between these balance-sheet variables and our dependent variables, we do not include them in the main regression.[15]

For robustness purposes, we also include three lags of the dependent variables in the regressions. The results are reported in Table 4.6. Our findings on the news score remain robust. However, we lose the explanatory power of the liquidity risk variable when we include the lagged CDS returns. This is reasonable given the direct relationship between CDS spreads and market funding and liquidity risk.

4.5.2 Panel Vector Autoregression (Panel VAR)

The panel regressions have established the significant explanatory power of our WSJ based news score on capturing the cross-sectional variations in equity returns, as well as CDS returns during the crisis period. The different reaction patterns between the equity and CDS returns, as well as between the crisis versus non-crisis periods, motivate us to explore further the causal (predictive) relationship between the media content variable and the returns (both CDS and equity). For this, we adopt the panel vector autoregression (panel VAR) model.

The standard time-series vector autoregression (VAR) model has been widely used in macro-econometrics to explore the interactions among various endogenous but interdependent variables.[16] Holtz-Eakin, Newey, and Rosen (1988) is the first attempt to introduce VAR in a panel data setting. Such a

[14]The equity volatility is significant on equity returns when we exclude the fixed effect.
[15]Relevant regression results are available upon request.
[16]Exogenous variables could also be included.

setting allows for non-stationary individual effects. The key difference between the traditional VAR versus the panel VAR is that the latter introduces a cross-sectional dimension, which takes into account the individual heterogeneity. Such feature makes the panel VAR to be preferred over the VAR model in micro studies in order to capture cross-sectional heterogeneity (Canova and Ciccarelli, 2013; Abrigo and Love, 2015).

Equation (4.2) displays the panel VAR regression setting. The endogenous variables are the news score and the CDS return, $Y_{i,t}^{k}$, when k = CDS (and the equity return when k = equity). Five lags of the endogenous variables are included. This lag length is chosen in accordance with the Bayesian Information Criteria. We also control for both heteroskedasticity and autocorrelation.

$$Y_{i,t}^{k} = \alpha_i^k + \sum_{l=1}^{5} \delta_{i,l}^{k} Y_{i,t-l}^{k} + \sum_{l=1}^{5} \gamma_{i,l}^{k} News_{i,t-l} + \epsilon_{i,t}^{k} \tag{4.2}$$
$$k \in \text{CDS return},\ \ \text{equity return}; \quad \forall i \in 1, ..., 31;$$

The hypotheses are as follows. First, if the price discovery happens in the equity market first, we should expect a faster reaction of equity returns to the news sentiment than the reaction of CDS returns. Any significance in the coefficients of the news score for equity returns should materialise prior to any significance in the news score for CDS returns. However, if the information flows from the CDS market to the equity market, we should expect to observe the opposite. Second, if the CDS market is filled with inattentive traders who have preferences for liquidity, it is reasonable to expect that the explanatory power of the news score improves for CDS returns during the crisis period. This is because there is higher liquidity risk during the crisis. A risk-averse CDS trader who trades for liquidity pays more attention to the news over this period in order to avoid losses. Hence, the reaction of CDS traders to news sentiment would be faster and stronger during the crisis than the non-crisis period.

Table 4.7 reports the coefficient statistics for equation (4.2). The first two columns report the results of the full sample. Columns 3 and 4 are the results of the crisis period, and the last two columns are the findings of non-crisis period. Columns 1, 3, and 5 (2, 4, and 6) are the coefficient statistics for CDS (equity) returns. For the full sample, the reaction of CDS returns to the media news occurs on the second day. One standard deviation increase in the news score significantly decreases the credit return by 4.9 percentage points. On the fourth day, CDS returns rebound back with a 5.4 percentage points increase. For the equity returns, the reaction happens much earlier than credit returns. We observe an immediate reaction of equity returns to the media content at the first lag. (The impulse response function shows that the reactions actually happen on the news event day.) With one standard deviation increase in the news score, stock returns increase on average by 12.1 percentage. The impact of the news is absorbed on the following day when stock returns drop by 13.7 percent. The coefficients of both lags are significant at 5 percent. The sufficient large scales of the coefficients also suggest that the news score has a considerable economic impact on the equity returns. Figure 4.1 plots the impulse response functions. Each impulse is a one standard deviation shock to the news score. The direct effect of such shock on the CDS returns is plotted in Figure 4.1a, and the effect on the equity returns is plotted in Figure 4.1b. It is clear that CDS returns react significantly to the news from day 1 to day 2, and recovers from day 2 to day 4. After day 4, the impact of the news starts to diminish. From day 6, the news impact on CDS returns reverses back to zero. The impulse response function of equity returns shows a more rapid and stronger reaction than the credit returns. The equity returns increase significantly on the day of news release. The absorption of such news impact is also much faster (day 5). Furthermore, comparing the crisis and non-crisis periods, equity returns always react on the first lag (and the second lag in the non-crisis period), while credit returns react on the second lag and the fifth lag (crisis period) or the fourth lag (the non-crisis period). This is in line with our assumption that equity returns react to media news much faster than credit returns if the information flow is led by the equity market. Our results are supportive of Hilscher, Pollet, and Wilson (2015): equity returns lead credit protection returns.

Next, we examine the behaviour of the credit protection returns in and out of the crisis period. Column 3 of Table 4.7 suggests that CDS returns start to react significantly to the news at the second lag, during the U.S. Great Recession. The reversal then happens at the fifth lag. Furthermore, the impact of the news sentiment during the crisis has a high economic significance, in comparison to the news impact in the non-crisis period. One standard deviation increase in the news score depresses credit protection returns by 19.4 percentage points two days after the news release. Credit returns recover back to normal levels after another three days with a 17.7 percent points increase. In the non-crisis period, CDS returns exhibit a much weaker reaction to the news score. The news sentiment only affects CDS returns at the fourth lag. The magnitude of such a coefficient is also small (i.e., 6 percentage points). Overall, the empirical findings suggest that traders in the CDS market tend to respond to media news in a more rapid fashion during the crisis.

In the lower part of Table 4.7, we report the χ^2 statistics of the panel VAR-Granger Causality Wald test. The null hypothesis is that excluding all news score variables does not Granger-cause the changes in the dependent variable (the CDS and equity returns). In all cases, we reject the null with statistically significance, and conclude that the news sentiment Granger-causes the movements in returns. Furthermore, we also perform an F-test on the panel VAR regressions with a null hypothesis that the sum of the coefficients corresponding to the five lags of news sentiment is equal to zero. In all cases, we fail to reject the null and conclude that there is full price reversal across all of the six empirical settings.

For robustness purposes, we run the panel VAR regression of equation (4.2) with control variables. We include exogenous risk factors (with one day lag). The risk factors are the ones used previously in the panel regression. We include the volatility premium, the equity volatility of individual firm, the U.S. stock market excess return, and the liquidity risk factor. The regression results are reported in Table 4.8. First, the main results on the equity and the credit returns do not change. The equity return illustrates a faster and more economic significant reaction to the news than the credit return, for the full sample, the crisis and non-crisis periods. Second, credit returns respond to the news at a more rapid speed and with a higher economic significance during the financial crisis than the non-crisis period.

With respect to the control variables, the U.S. stock market remains the most important global risk factor. It is statistically and economically significant for both credit and equity returns, except for equity returns during the non-crisis period. Furthermore, the signs are consistent with the negative relationship between the CDS and equity returns. That is, an increase in the stock market return decreases CDS returns and increases equity stock returns. The behaviour of the liquidity risk is also worthy of mention. We observe a significant influence of the liquidity risk on CDS returns during the financial crisis period, but not during the non-crisis sample. This result confirms that the CDS market is sensitive to the deterioration of market liquidity conditions during the Great Recession. The increasing significance of the liquidity risk, together with the simultaneous improvement of CDS traders' attention to news, tends to support the inattention theory proposed in the literature. The inattention of the CDS traders causes the delay in the CDS returns' response to new information releases, in comparison to the equity market. During the financial crisis, the preferences for liquidity of credit traders force them to pay more attention to market news, which leads to a more rapid reaction to news sentiment in the CDS market.

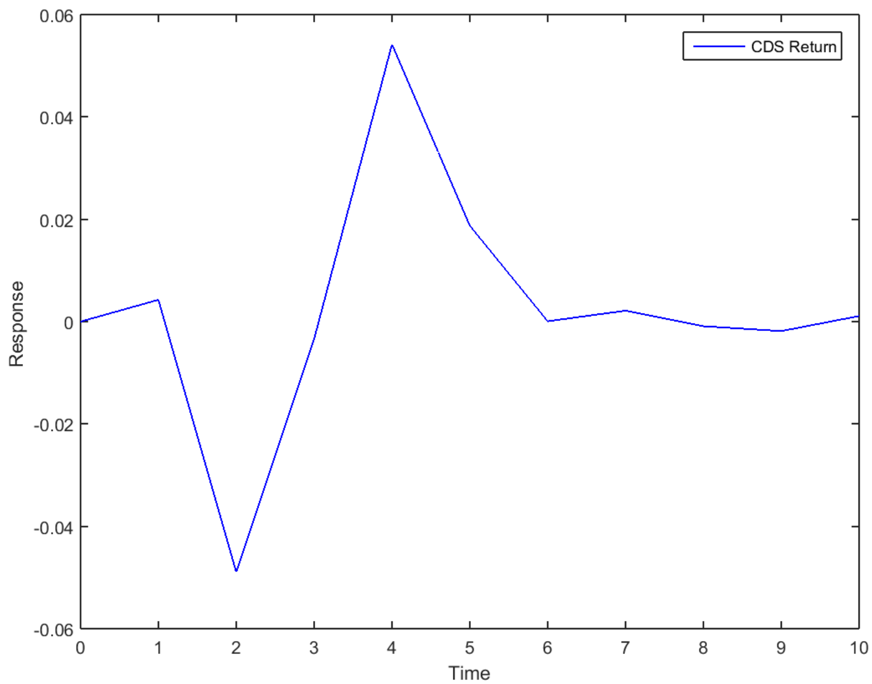
4.6 Conclusion

In this paper, we study the impact of firm-specific news sentiment on the credit and equity returns of 31 U.S. financial firms. We perform a standard linguist analysis algorithm on news articles published by the Wall Street Journal and construct a news score variable for each firm. We then exam the reactions of credit and equity returns to the news score by using the panel and panel VAR regressions. We find that CDS returns exhibit a delay in responding to the news, in comparison to equity returns. We further separate the sample into crisis and non-crisis periods. The regression results based on the sub-samples suggest that CDS returns respond to the news more quickly during the financial crisis than the non-crisis period. The improvement in the news reaction of CDS returns is accompanied by a simultaneous increase in the significance of the market liquidity risk.

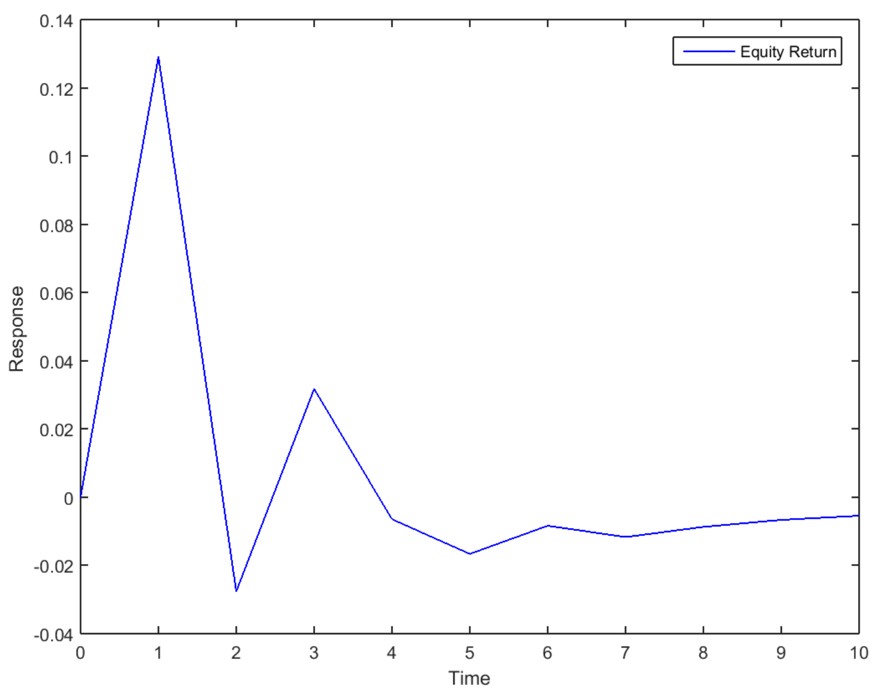
Our results are supportive of the findings of Garcia (2013). News sentiment impact tends to concentrate during recessions. We provide evidence showing that such phenomenon also exists in the credit derivative market. Furthermore, this paper is closely linked to Hilscher, Pollet, and Wilson (2015) and Mamaysky and Glasserman (2016). In particular, our empirical findings suggest an explanation related to investor inattention. Hilscher, Pollet, and Wilson (2015) argue that informed traders would prefer to trade in the equity market due to high transaction costs in the CDS market, whereas credit market is used by liquidity traders for non-fundamentals based reasons. Therefore, the CDS traders pay less attention to news development than the equity traders, which explains the delayed response in the credit returns. During the financial crisis, the credit market liquidity deteriorates, which causes risk-averse CDS traders to become more attentive to news information in order to avoid potential losses. This explains the faster response of CDS returns to news sentiment during the crisis period, and the increasing significance of the liquidity risk factor.

Finally, to provide direct evidence for the inattention theory, a substantial amount of research efforts is required. Firstly, if credit traders are mainly liquidity traders, it would be ideal to construct a liquidity news sentiment based on advanced linguist analysis. The algorithm provided by Liebmann, Orlov, and Neumann (2016) is an excellent example to build dynamic corpus and lexicon with particular preferences.[17] If the hypothesis is true, we should expect a more rapid reaction to the liquidity news from CDS traders. Alternatively, exogenous shocks to the market liquidity condition can be used to establish causality relationship between the news and the CDS returns. Examples include government regulations and policy or protocol reforms. Secondly, this paper is a preliminary study based on 31 U.S. financial firms. It is essential to enlarge the firm sample to include both financial and non-financial corporations. Thirdly, the full recovery of equity and CDS returns suggest that the constructed news score contains only noise but no new information. We believe this could be due to the limited number of articles used in the analysis. In future work, we will focus on improving the news sentiment variable by including more news articles from different journals and resources (such as Reuters and Bloomberg News). Furthermore, we will also work on building a more direct linkage between price discovery and news reaction.

[17] The authors use capital returns as a measure to determine positive and negative lexicon. Similar criteria could be adopted to construct positive and negative corpus for liquidity risk by using the market liquidity or funding cost as a criterion.



(a) CDS returns



(b) Equity Return

Figure 4.1. Impulse Response Function: CDS and Equity Returns

Table 4.1. Financial Firms included in the Wall Street Journal News Sample

	S&P 500 Financial Firms	Markit CDS Ticker
1	American Express Co	AXP
2	American International Group Inc	AIG
3	Aon PLC	AOC
4	Bank of America Corp	BACORP
5	Bank of New York Mellon Corp	BNYMEL
6	BB & T Corp	BBT
7	Berkshire Hathaway Inc	BRK
8	Capital One Financial Corp	COF
9	Charles Schwab Corp	SCH
10	Citigroup Inc	C
11	Fifth Third Bancorp	FITB
12	Goldman Sachs Group Inc	GS
13	JPMorgan Chase & Co	JPM
14	KeyCorp	KEY
15	Legg Mason Inc	LM
16	Loews Corp	LTR
17	Marsh & McLennan Cos Inc	MMC
18	MetLife Inc	MET
19	Morgan Stanley	MWD
20	PNC Financial Services Group Inc	PNC
21	Prudential Financial Inc	PRU
22	Simon Property Group Inc	SPG
23	State Street Corp	STT
24	SunTrust Banks Inc	STI
25	The Allstate Corp	ALL
26	The Hartford Financial Services Group Inc	HIG
27	Travelers Cos Inc	TRV
28	US Bancorp	USB
29	Vornado Realty Trust	VNO
30	Wells Fargo	WFC
31	Weyerhaeuser Co	WY

Table 4.2. Summary Statistics

The table reports the summary statistics of the single-name 5-year CDS spread on the 31 financial firms. The statistics include mean, standard deviation (SD), minimum, maximum and Number of observations (N). All measures are in basis points. The sample period ranges from 3rd January 2001 to 14 June 2016.

Firm Name	Mean	SD	Minimum	Maximum	N
American Express Co	78.02	91.57	8.07	700.07	3884
American International Group Inc	202.24	392.00	8.25	3647.57	3836
Aon PLC	69.50	55.27	23.45	446.87	3793
Bank of America Corp	121.41	90.09	8.09	498.33	2629
Bank of New York Mellon Corp	69.51	31.54	10.02	143.40	2254
BB&T Corp	72.78	47.44	12.62	254.00	3707
Berkshire Hathaway Inc	89.79	82.07	6.80	526.80	3162
Capital One Financial Corp	150.64	139.74	21.75	1051.67	3667
Charles Schwab Corp	50.22	25.91	15.73	141.19	3597
Citigroup Inc	101.76	101.68	6.83	662.86	3846
Fifth Third Bancorp	245.71	45.67	175.38	325.01	1598
Goldman Sachs Group Inc	103.47	82.29	17.90	595.84	3885
JPMorgan Chase	72.86	40.18	11.33	237.91	2997
KeyCorp	132.25	144.38	12.00	618.80	3490
Legg Mason Inc	70.08	45.87	14.50	203.33	3350
Loews Corp	58.94	31.49	10.82	178.26	3835
Marsh & McLennan Cos Inc	59.46	30.80	16.51	277.53	3134
MetLife Inc	133.76	148.33	10.54	996.19	3603
Morgan Stanley	124.39	125.20	17.30	1438.59	3880
PNC Financial Services Group Inc	71.26	49.67	18.27	307.65	3172
Prudential Financial Inc	138.89	172.91	10.56	1323.77	3511
Simon Property Group Inc	102.85	114.01	14.80	900.00	3761
State Street Corp	138.51	78.89	14.30	250.50	2891
SunTrust Banks Inc	90.92	80.90	9.58	422.95	3821
The Allstate Corp	60.71	55.48	8.92	411.25	3613
The Hartford Financial Services Group Inc	139.26	166.93	9.53	1161.54	3546
Travelers Cos Inc	66.81	33.51	16.73	169.94	2342
US Bancorp	58.81	43.18	7.50	249.64	3581
Vornado Realty Trust	129.91	136.72	29.15	982.50	3240
Wells Fargo	60.14	45.69	6.22	315.26	3827
Weyerhaeuser Co	105.76	59.36	23.03	354.21	3826

Table 4.3. Pooled Vector Autoregression: Full Sample

The following table reports the coefficient statistics from pooled Vector Autoregression for daily equity and CDS protection returns. All regressions include year effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

			CDS Return (t)			**Equity Return (t)**	
CDS Return	**Y (t-1)**	0.128***	0.115***	0.113***	-0.028***	-0.025***	-0.025***
		(7.871)	(6.975)	(6.823)	(-3.310)	(-2.960)	(-2.919)
	Y (t-2)		0.070***	0.065***		-0.020**	-0.021**
			(4.271)	(3.914)		(-2.330)	(-2.395)
	Y (t-3)			0.027			-0.015*
				(1.624)			(-1.789)
Equity Return	**Y (t-1)**	-0.243***	-0.241***	-0.240***	0.006	0.006	0.005
		(-7.625)	(-7.581)	(-7.555)	(0.390)	(0.338)	(0.291)
	Y (t-2)		-0.059*	-0.059*		0.000	-0.001
			(-1.827)	(-1.830)		(0.009)	(-0.069)
	Y (t-3)			-0.032			-0.0385*
				(-1.012)			(-1.328)
N		3,883	3,882	3,881	3,883	3,882	3,881

Table 4.4. Pooled Vector Autoregression: Sub Samples

The following table reports the coefficient statistics from a pooled Vector Autoregression for daily equity and CDS protection returns. All regressions include year effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period on the top panel ranges from 3rd January 2001 to 31 December 2007. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

Prior Sample: January 2001 to December 2007							
		CDS Return (t)			**Equity Return (t)**		
CDS Return	**Y (t-1)**	0.042*	0.038	0.036	-0.013	-0.012	-0.011
		(1.756)	(1.572)	(1.477)	(-1.231)	(-1.103)	(-1.040)
	Y (t-2)		0.047**	0.045*		-0.011	-0.011
			(1.975)	(1.854)		(-1.056)	(-1.070)
	Y (t-3)			0.051**			-0.019*
				(2.149)			(-1.809)
Equity Return	**Y (t-1)**	-0.222***	-0.222***	-0.220***	-0.046*	-0.045*	-0.046*
		(-4.032)	(-4.030)	(-3.997)	(-1.895)	(-1.879)	(-1.900)
	Y (t-2)		-0.035	-0.034		0.014	0.012
			(-0.639)	(-0.616)		(0.579)	(0.497)
	Y (t-3)			-0.008			-0.062
				(-0.136)			(-1.354)
N		1,755	1,754	1,753	1,755	1,754	1,753

Crisis Sample: January 2008 to December 2009							
		CDS Return (t)			**Equity Return (t)**		
CDS Return	**Y (t-1)**	0.122***	0.110***	0.107***	-0.026***	-0.023***	-0.023***
		(6.934)	(6.206)	(6.039)	(-3.181)	(-2.787)	(-2.725)
	Y (t-2)		0.067***	0.061***		-0.019**	-0.019**
			(3.794)	(3.396)		(-2.310)	(-2.310)
	Y (t-3)			0.039**			-0.014*
				(2.202)			(-1.733)
Equity Return	**Y (t-1)**	-0.254***	-0.253***	-0.250***	-0.002	-0.003	-0.003
		(-6.749)	(-6.723)	(-6.667)	(-0.132)	(-0.165)	(-0.196)
	Y (t-2)		-0.058	-0.058		0.010	0.009
			(-1.519)	(-1.529)		(0.578)	(0.499)
	Y (t-3)			-0.043			-0.031*
				(-1.144)			(-1.724)
N		505	505	505	505	505	505

Table 4.5. Panel OLS Regression

The following table reports the coefficient statistics from a panel regression for daily equity and CDS protection returns. The explanatory variables include the media news sentiment, the U.S. volatility premium, 30-day realised equity volatility of each firm, U.S. stock excess return and liquidity risk. The news score measure is based on textural analysis algorithm. All regressions include both year effect and fixed effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
NewsScore	0.003	0.040**	-0.165**	0.315***	0.016	0.036**
	(0.092)	(2.569)	(-2.003)	(3.427)	(0.447)	(2.408)
Volatility premium	0.146***	0.036**	0.052	0.191**	0.177***	-0.021
	(5.810)	(2.573)	(1.568)	(2.419)	(5.051)	(-1.396)
Equity volatility	0.125***	0.001	0.065	-0.064	0.250***	-0.029
	(3.214)	(0.061)	(1.544)	(-1.332)	(3.482)	(-1.050)
US stock market	-0.481***	1.341***	-0.482***	1.872***	-0.521***	1.159***
	(-8.455)	(22.798)	(-6.798)	(16.359)	(-7.969)	(21.296)
Liquidity risk	0.028	0.009*	0.089***	0.011	0.016	0.008*
	(1.574)	(1.698)	(2.667)	(0.141)	(0.891)	(1.815)
Constant	0.115***	-0.012***	0.405***	-0.386***	0.075***	-0.009**
	(16.835)	(-3.018)	(19.216)	(-3.275)	(10.227)	(-2.408)
Adjusted R^2	0.035	0.426	0.028	0.354	0.044	0.483
N	102,282	102,282	13,978	13,978	88,304	88,304

Table 4.6. Panel OLS Regression: with Lagged Dependent Variables

The following table reports the coefficient statistics from a panel regression for daily equity and CDS protection returns. The explanatory variables include the media news sentiment, the U.S. volatility premium, 30-day realised equity volatility of each firm, U.S. stock excess return and liquidity risk. Three lags of the dependent variables are included for robustness purpose. The news score measure is based on textural analysis algorithm. All regressions include both year effect and fixed effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
NewsScore	0.009	0.043***	-0.150*	0.267***	0.021	0.037**
	(0.286)	(2.658)	(-1.903)	(2.981)	(0.598)	(2.461)
Y (t-1)	0.039	-0.008	0.046	0.100**	0.033	-0.015***
	(1.215)	(-0.487)	(1.332)	(2.064)	(0.827)	(-2.594)
Y (t-2)	0.042***	-0.007	0.018	0.005	0.054***	0.001
	(3.521)	(-0.981)	(1.112)	(0.270)	(5.335)	(0.321)
Y (t-3)	-0.000	-0.033***	-0.002	-0.043**	-0.001	-0.010***
	(-0.011)	(-7.692)	(-0.231)	(-2.318)	(-0.076)	(-3.220)
Volatility premium	0.154***	0.042***	0.057*	0.200**	0.186***	-0.018
	(5.588)	(2.898)	(1.710)	(2.574)	(5.086)	(-1.171)
Equity volatility	0.118***	-0.001	0.061	-0.063	0.242***	-0.030
	(3.214)	(-0.057)	(1.527)	(-1.319)	(3.434)	(-1.083)
US stock market	-0.475***	1.346***	-0.478***	1.920***	-0.513***	1.161***
	(-8.541)	(22.576)	(-6.808)	(15.836)	(-7.972)	(21.133)
Liquidity risk	0.024	0.010*	0.063	0.085	0.017	0.008*
	(1.332)	(1.821)	(1.443)	(1.057)	(0.952)	(1.712)
Constant	0.105***	-0.011***	0.375***	-0.301**	0.069***	-0.009**
Adjusted R^2	0.039	0.427	0.030	0.367	0.048	0.484
N	102,189	102,189	13,978	13,978	88,211	88,211

Table 4.7. Panel Vector Autoregression for CDS and Equity Returns

The following table reports the coefficient statistics from a panel vector autoregression (VAR) for daily equity and CDS protection returns on the news sentiment score variable. The news variable is constructed based on textual analysis algorithm. Regressions controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The t-statistics are reported in parentheses. The full sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
Y (t-1)	0.038***	-0.065***	0.050**	-0.096***	0.031*	-0.042***
	(2.780)	(-6.113)	(2.283)	(-4.338)	(1.734)	(-7.032)
Y (t-2)	0.044***	-0.015	0.024*	-0.066***	0.057**	0.018***
	(2.831)	(-1.241)	(1.776)	(-3.217)	(2.458)	(3.245)
Y (t-3)	-0.002	-0.032***	-0.003	-0.049***	0.000	-0.013**
	(-0.300)	(-3.090)	(-0.329)	(-2.850)	(0.004)	(-2.403)
Y (t-4)	-0.009	-0.039***	-0.011	-0.083***	-0.009	0.004
	(-1.240)	(-4.033)	(-1.068)	(-5.386)	(-0.830)	(0.873)
Y (t-5)	-0.006	-0.030***	-0.004	-0.021	-0.007	-0.045***
	(-1.150)	(-3.255)	(-0.425)	(-1.361)	(-1.205)	(-9.067)
NewsScore(t-1)	0.004	0.121**	0.094	0.710**	-0.010	0.083**
	(0.176)	(2.495)	(0.989)	(2.422)	(-0.425)	(2.379)
NewsScore(t-2)	-0.049**	-0.137**	-0.194*	-0.513	-0.025	-0.085*
	(-1.988)	(-2.249)	(-2.191)	(-1.327)	(-1.050)	(-1.888)
NewsScore(t-3)	-0.003	0.051	0.128	-0.178	-0.013	0.047
	(-0.170)	(0.852)	(1.504)	(-0.474)	(-0.708)	(1.081)
NewsScore(t-4)	0.054***	0.009	0.026	0.063	0.060***	0.018
	(2.697)	(0.158)	(0.289)	(0.169)	(3.200)	(0.419)
NewsScore(t-5)	0.022	-0.048	0.177*	-0.160	-0.005	-0.028
	(0.931)	(-0.986)	(1.926)	(-0.521)	(-0.202)	(-0.859)
Chi2 (5) [Joint]	11.892	11.068	10.524	10.187	12.146	12.411
p-value	0.036	0.05	0.062	0.07	0.033	0.03
N	105,061	105,061	15,150	15,150	89,911	89,911

Table 4.8. Panel Vector Autoregression for CDS Return and Equity Return: Robust Control

The following table reports the coefficient statistics from a panel vector autoregression (VAR) for daily equity and CDS protection returns on the news sentiment score variable. Additional exogenous variables with one day lag are included: the U.S. volatility premium, 30-day realised equity volatility, U.S. stock excess return and liquidity risk. Regressions controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The t-statistics are reported in parentheses. The full sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
Y (t-1)	0.023	-0.050***	0.035*	-0.062**	0.012	-0.027***
	(1.629)	(-3.143)	(1.690)	(-2.406)	(0.655)	(-3.291)
Y (t-2)	0.046***	-0.023*	0.025*	-0.049**	0.059**	0.009
	(2.821)	(-1.922)	(1.846)	(-2.357)	(2.442)	(1.581)
Y (t-3)	-0.002	-0.028***	-0.003	-0.036**	-0.001	-0.022***
	(-0.345)	(-2.693)	(-0.331)	(-2.054)	(-0.247)	(-4.144)
Y (t-4)	-0.008	-0.047***	-0.009	-0.076***	-0.009	-0.006
	(-1.006)	(-4.768)	(-0.911)	(-4.642)	(-0.789)	(-1.223)
Y (t-5)	-0.006	-0.028***	-0.006	-0.012	-0.008	-0.055***
	(-1.094)	(-3.065)	(-0.621)	(-0.809)	(-1.255)	(-10.784)
NewsScore(t-1)	-0.001	0.138***	0.070	0.585*	-0.011	0.086**
	(-0.049)	(2.795)	(0.739)	(1.921)	(-0.443)	(2.450)
NewsScore(t-2)	-0.042*	-0.134**	-0.182*	-0.481	-0.024	-0.087*
	(-1.698)	(-2.195)	(-1.806)	(-1.216)	(-0.991)	(-1.919)
NewsScore(t-3)	-0.002	0.033	0.135	-0.136	-0.012	0.048
	(-0.091)	(0.547)	(-1.596)	(-0.357)	(-0.629)	(1.083)
NewsScore(t-4)	0.060***	0.008	0.032	-0.029	0.063***	0.015
	(2.941)	(0.141)	(0.368)	(-0.077)	(3.350)	(0.352)
NewsScore(t-5)	0.016	-0.041	0.158*	-0.152	-0.005	-0.023
	(0.700)	(-0.828)	(1.722)	(-0.483)	(-0.215)	(-0.696)
Volatility premium	0.062***	0.005	0.065**	-0.056	0.066***	0.042***
	(-3.492)	(0.351)	(-2.033)	(-1.522)	(-2.935)	(3.753)
Equity volatility	0.030	0.027**	-0.019	0.042**	0.134**	-0.005
	(1.305)	(1.961)	(-1.208)	(1.986)	(2.297)	(-0.504)
US stock market	-0.437***	0.047*	-0.442***	0.134**	-0.437***	0.002
	(-16.983)	(-1.688)	(-9.509)	(-2.297)	(-14.535)	(-0.136)
Liquidity risk	0.015	0.029***	0.120**	0.067	-0.001	0.021***
	(0.993)	(3.140)	(1.979)	(1.528)	(-0.068)	(2.810)
Chi2 (5) [Joint]	11.726	12.233	9.265	9.205	12.157	11.136
p-value	0.039	0.032	0.099	0.091	0.033	0.049
N	102,097	102,097	13,978	13,978	88,119	88,119

Chapter 5

The Impacts of Financial Liberalisation on House and Land Prices: Evidence from China

5.1 Introduction

When the U.S. housing market reached its peak in 2006, few expected that the collapse of the sub-prime mortgage market would lead to a worldwide economic recession. From 2007 to 2009, the crashed house prices and the subsequent financial crisis destroyed $19.7 trillion worth of assets owned by U.S. households. The bankruptcies of several financial institutions in 2008 (e.g., Bear Stearns, Lehman Brothers), which augmented the instability of the global financial system, marked the onset of a severe global recession. The 2007 financial crisis highlights the crucial connection between the real estate market and the development of a nation's finance and economy. Leamer (2007, 2015) and Ghent and Owyang (2010) show that house price is a crucial precursor of a nation's business cycle: a fall in the residential investment is a reliable harbinger of a recession. Furthermore, the authors suggest that any policy intervention during an economic recession should focus on the housing market to restore residential investment.

China, as the second largest economy in the world, has served as the major engine for global economic growth during the past decade. Meanwhile, the nation's real estate market has been experiencing an unprecedented price boom. Figure 5.1 displays the logarithm of the average real house price across 31 provinces in China from 1999 to 2014. The average real house price in China has tripled during the past 15 years, from 1508.6 Yuan per square metre in 1999 to 4467.1 Yuan per square metre in 2014.[1] The 15-year growth rate of the U.S. residential property real price was only 80 percent from 1999 to 2006, right before the subprime crisis. Soaring house prices over the past decade have drawn the attention of global economists and policy authorities, who are concerned about a potential housing bubble. A main concern is that the burst of this bubble would lead to a meltdown of China's real estate market. This could severely damage its economy and contagiously harm the global economy, which has just recovered from a series of crises that originated in the U.S. and Europe. Therefore, it is crucial to understand the determinants that contribute to China's rapidly rising house prices.

This paper investigates the impact of the credit supply available to residential investments on the

[1] Yuan is the basic unit of the official currency of China, which is Renminbi (RMB).

real estate market. The findings of this paper contribute to the literature on the causal relationship between credit supply and asset price. Mian and Sufi (2009); Favara and Imbs (2015); Adelino, Schoar, and Severino (2012); Glaeser, Gottlieb, and Gyourko (2013) and Di Maggio and Kermani (2015) find that a change in the equilibrium credit level affects the house price. In this study, the U.S. financial crisis of 2008 is used as an exogenous shock to the household credit supply in China. The variation in the exposure to the financial crisis across difference provinces in China is used to study whether credit can affect housing and land prices locally. In particular, the deregulation process of China's financial market in opening up its local currency business to foreign banking institutions is used for the identification strategy. It is crucial to point out that the deregulation itself is not exogenous. Rather, the identification strategy relies on the status of the control group: firstly, provinces in the control group are unaffected by deregulation because of their geographical locations; secondly, they should not respond to the deregulation if the financial liberalisation only constitutes a credit supply shock. However, they could response to the deregulation if such an event reflects changes in the demand for credit.

The event of interest marks the regulatory changes that opened up the Renminbi business to foreign banks. Renminbi (RMB hereafter) is the official currency of the People's Republic of China. In the early 1990s, there were already a large number of foreign banks operating in China, though their activities were largely confined to foreign currency and RMB transactions for foreign clients. Since 1996, China has gradually lifted geographical and customer restrictions on foreign banking institutions' operations. For example, in 1998, Shanghai was the only city that allowed foreign banks to conduct RMB businesses. In 1998, a second city, Shenzhen, was added to the list. In 2006, the central government completely opened up the RMB business to locally incorporated foreign banks. Foreign banks in every province could offer products such as credit cards and mortgage loans to domestic citizens. By the end of 2006, 74 foreign banks from 22 countries and regions operated 200 branches and 79 sub-branches in 25 cities in China (CBRC, 2007). According to Hongyuan and Wang (2007), credit business (including both domestic and foreign currencies) provided by foreign banks in China achieved 514.3 billion RMB by the end of May, 2007. Compared to 2001, the size of foreign credit in China expanded by 2.39. Lin (2011) studies the impact of foreign bank entry on domestic firms' access to bank credit, and finds that non-state-owned firms benefit the most from foreign banks' credit. The author uses a within-country staggered geographic variation in the policy of foreign bank lending in China. It is reasonable to consider that the opening-up of RMB business to foreign banks constitutes positive credit supply shocks to domestic residents and enterprises. A province where more foreign banking institutions are established experiences a larger upward shock in the credit provision. When the housing supply is inelastic, an increase in the credit supply positively affects the house price (Favara and Imbs, 2015). Therefore, the house prices of more financially liberalised provinces appreciate more. However, it is also crucial to point out that the presence of the foreign banks could have no impact on the local house price at all. This is because foreign banks are a small component of the total local lending in China. According to the annual report published by CBRC (2008), the total assets of foreign banks by the end of 2007 were RMB 1253 billion, accounting for 2.38% of China's total banking assets.

However, the impact of financial liberalisation is a double-edged sword. Studies by Takats (2010) and De Haas and Van Horen (2013) show that cross-border bank lending dropped sharply during the U.S. financial crisis. In particular, the credit contrast is mainly caused by the supply side of the financial market, instead of the demand side. A province that is more financially liberalised towards foreign banking institutions should experience a sharper contrast in the credit supply, leading to more severe price depreciation in its property market.

This paper is also related to the literature on the geographic determinants of house price, such as Saiz (2010) and Gyourko, Saiz, and Summers (2008). The geographic features of land surface exogenously determine the relative scarcity of land that is suitable for residential or commercial construction. A measure that captures the proportion of undevelopable land over total geographic surface of each province is constructed. The undevelopable land is calculated as the sum of the surface areas that correspond to lakes, rivers, wetlands, afforested land and agricultural land. A higher proportion of undevelopable land over the total administrative area suggests that the province is more geographically constrained for urban land development and has higher inelasticity level of its housing supply. A higher supply inelasticity will amplify the negative effect of financial crisis. The findings show that houses are more expensive in provinces with less available land for construction. Such provinces also experience larger house price depreciations during the financial crisis, increasing with the degree of financial liberalisation. That is, the house price of a province declines more during the financial crisis when the province is more geographically constrained and more financially open.

In addition, this paper compares the simultaneous impacts of credit supply on the land and house prices. The findings of this paper highlight the relative importance of land in the urban economic development. Following similar logic to the housing market, credit expansion is expected to facilitate the price appreciation of land. As the supply of land is largely inelastic, and the real estate price includes the value of land (Kiyotaki, Michaelides, and Nikolov, 2011), land price should react to credit expansion, which is caused by the financial deregulation, to a larger extent than house price does. The results show that financial deregulation positively impacts both land and house prices. For the same province, the land price appreciates more than the house price.

The rest of this chapter is organised as follows. Section 5.2 elaborates the background and the hypotheses development. Section 5.3 presents data resources, the construction of housing and land prices, and other variables. Section 5.4 presents the regression results regarding the impacts of financial crisis and credit supply on house and land prices. Section 5.5 concludes.

5.2 Hypotheses Development

The literature suggests that the supply of credit to residential investments contributes to explaining the house price movement. Several studies (Mian and Sufi, 2009, 2010, 2014) claim that the expansion of sub-prime mortgage credit is the main factor that caused the housing bubble in the U.S. real estate market between 2002 and 2005. Adelino, Schoar, and Severino (2012) find that policy changes in the Conforming Loan Limit (CLL) by the commercial banks facilitate the flows of cheap credit and have significant influences on the house prices. The price influence is more profound around the loan limit level. A recent study by Favara and Imbs (2015) suggests that credit expansion, which is measured in terms of size and standard of a mortgage loan, boosts residential housing demands and pushes up the real estate price. To investigate the impact of credit supply on China's property market, a similar empirical identification strategy as the Tripathy (2015) is employed in this study. The regulatory reforms of the country's banking sector are used to identify the degree of financial openness for the 31 provinces across China. In particular, this study focuses on the legal documents issued by the Chinese Banking Regulation Commission (CBRC) regarding foreign banks' RMB business operation. The following paragraph provides a brief summary of the banking deregulation process.

The opening-up of China's banking sector towards the West can be divided into three phases: 1980-1993, 1994-2001 and 2002-2006 (CBRC, 2007). The establishment of the representative office of the Japan Import and Export Bank in Beijing in 1979 marked the beginning of China's financial liberalisation process. By the end of the 1990s, there were a large number of foreign banking institutions operating in China. However, their activities were highly confined to foreign currency and RMB transactions for foreign investors. To prepare for the accession to the World Trade Organisation (WTO), China had accelerated the pace of liberalisation in its banking industry. The Chinese authority gradually lifted geographical and customer restrictions on foreign banking institutions. In December 1996, for the first time, the CBRC granted foreign banks access to the local currency (RMB) business, by issuing *'The Provisional Regulations on Foreign Banking Institutions Renminbi Business on a Trial Basis in Shanghai Pudong Area'* (CBRC, 1996). In 1998, following Shanghai, Shenzhen became the second pilot city to allow foreign banks to conduct RMB business. In 2001, China joined the WTO. This signalled the phased-in deregulation of foreign banking operations. There was a five-year grace period under the WTO agreement. During this period, the Chinese government amended and issued a series of laws and regulations regarding foreign banking institutions (CBRC, 2007). In 2001, Tianjin and Dalian joined Shanghai and Shenzhen as cities allowing foreign banks to conduct RMB business. In 2005, this was expanded to foreign banks located in Guangzhou, Zhuhai, Qingdao, Nanjing and Wuhan in 2002; Jinan, Fuzhou, Chengdu and Chongqing in 2003; Kunming, Beijing, Xiamen, Shenyang and Xi'an in 2004; and Shantou, Ningbo, Harbin, Changchun, Lanzhou, Yinchuan, and Nanning. On 11 December 2006, China removed all geographical, customer and product restrictions on foreign banking institutions' operations, honouring its commitments to

WTO. This was accompanied by the removal of all non-prudential market access restrictions such as the ownership and juridical forms requirements. The complete deregulation of 2006 meant that foreign banks had been granted full access to the Chinese market. Figure 5.3 depicts the total number of foreign financial institutions and the new entry of foreign financial institutions from 1980 to 2006 (CBRC, 2007; He and Yeung, 2011). The number of new entrants grew smoothly in the early 1990s, but started to drop around the Asian Financial Crisis. Aligning with the opening process of the banking sector, a massive increase in the number of new entrants emerged in 2002 and continued until 2006.

The year 2006 marked a new era in China's banking system. Following this regulatory liberalisation, foreign banks were permitted to offer similar financial services and products as Chinese banks and were to be treated and regulated in the same way as domestic banks. Most importantly, foreign banks were allowed to offer RMB banking services to residential Chinese citizens and corporations, such as credit cards and mortgage loans. Therefore, the presence of foreign banking institutions conducting the RMB business prior to 2006 indicates the level of financial openness of individual province, and can be treated as an exogenous shift in the supply of local household credit. To construct the measure of financial openness, the number of foreign banking institutions, including representative offices, branches and sub-branches, inside each province by the end of 2006 is calculated. Figure 5.4 displays the geographical location pattern of foreign banking institutions across mainland China. Foreign financial institutions tend to cluster in provinces that are relatively financially liberalised. When more foreign banks establish their offices in a province, the citizens, residents and corporations of that province benefit with more choices of credit suppliers to offer mortgage loans. If an increase in the credit supply positively impacts the house prices, the aforementioned province would have higher house prices than a province with fewer or no foreign bank offices.[2] Therefore, the coefficient between financial openness and the local house price is expected to be positive.[3]

The financial turmoil of 2008 highlighted the fact that a banking panic can destroy the worldwide economy and cause severe recession. Studies by Claessens and Horen (2014); Takats (2010) and De Haas and Van Horen (2013) show that the financial crisis dramatically halted foreign direct investment in the banking sector. During the financial crisis, foreign banks reduced the credit business more than their domestic competitors. As the U.S. financial crisis is completely exogenous to China's economy, this study treats it as an external shock to examine the impact of credit supply on house and land prices. The financial crisis affected the real estate market of China negatively. The negative shock of a financial crisis can impact both the demand and supply sides of the property market. This chapter focuses on the impact on the supply side. If credit expansion introduced by financial deregulation increases the house prices in China, a province that is more financially liberalised prior to the crisis is expected to have a larger shrinkage in its foreign credit supply during

[2] Hereafter, the term 'bank office' refers to representative office, branch or sub-branch of a foreign bank.

[3] Similar reasoning applies to the land price.

the crisis.[4] This leads to larger price depreciation in its housing market.

H1: The real estate market experiences a higher price appreciation in a more financially open province, but suffers more severe price depreciation during the financial crisis of 2008. That is, provinces with higher participation rates of foreign banks experience higher house price volatilities during the U.S. financial crisis.

As the most basic of all economic resources, land is fundamental to a country's economic development. Kiyotaki, Michaelides, and Nikolov (2011) show that land as an input to tangible assets production is more important than capital. Such relative importance of land can intensify the impacts of labour productivity and interest rate on the house prices. In most developing countries, land is not only the primary means of generating a livelihood, but also the main vehicle for investment, accumulating wealth, and transferring wealth between generations (Deinlnger and Binswanger, 1999). On the supply side of the property market, the price paid for acquiring the usage right of a piece of land serves as the primary cost for real estate developers and construction firms. Therefore, the credit expansion introduced by the deregulation process also provides foreign credit to real estate developers and construction firms. This in turn boosts the demand of land for new property and infrastructure construction projects. Figure 5.1 plots the time series of logarithms of average real land and house prices across 31 provinces of China from 1999 to 2014. The growth rate of the average real land price is substantially higher than the growth rate of the average real house price. Recall that the real house price tripled over the past 15 years, the real price of land in China increased by 13 times during the same period, from only 93 Yuan per square metre in 1999 to 1293 Yuan per square metre in 2014. Figure 5.2 displays the logarithms of average real land prices for Beijing and Gansu. Beijing (Gansu) experienced the largest (smallest) land price appreciation from 103 (70) Yuan per square metre to 9800 (200) Yuan per square metre. In addition, the average land price illustrated its steepest climb between 2006 and 2007. Therefore, the financial deregulation also contributed positively to land price movement in China. A more financially liberalised province is expected to have a higher land price growth. In addition, the impact scale of credit expansion on the land price is expected to be larger than the one on the house price of the same province, due to the relative importance of land in the urban economy development.

H2: The land market experiences higher price appreciation in a more financially liberalised province. For the sample province, the impact of credit supply on the land price is larger than the impact on the house price.

In China, land and house prices are also tightly linked to the public finance. Construction and real estates are the main sectors that boost local GDP growth. Furthermore, GDP performance

[4] More financially liberalised/open/deregulation means the province has a larger number of foreign banking institutions by the end of 2006.

is the main evaluation criteria for a local governor's career promotion (Gao, Ru, and Tang, 2016; Qian and Roland, 1998). These facts motivate both central and local governments to actively engage in the housing market. Since the 1994 fiscal reform, local governments have reduced sources of budget revenue, while the budget expenditures increase with inflation. Since then, high budget deficits have been a common fiscal pressure facing Chinese cities. Meanwhile, local governments are the monopoly suppliers of urban land (Wu, Feng, and Li, 2015; Wei, Fang, Gu, and Zhou, 2015). As a consequence, land lease sales have become an increasingly important source of off-budgetary revenue for local governments. As the quantity of land supply for sale and lease is highly restricted by regulations and geographic location, local governments tend to increase the land price to gain higher profits. Wu, Feng, and Li (2015) show that budget deficit has a positive effect on land prices by using data on 35 major cities in China. Furthermore, unlike western countries, Chinese local sovereigns are not permitted to issue debt directly.[5] Hence, local governments establish separate investment units by pledging land and future land sales revenue as collaterals. The units issue bonds based on these collaterals, and provide capital to local governments to fund large scale investments. Therefore, it is uncontroversial to argue that a province with a higher public budget deficit could have higher land and house prices.

However, the important role of land in the local government's balance sheet became more critical during the U.S. financial crisis. Right after Lehman Brother's default in September 2008, China's exports to the U.S. dropped substantially. For this reason, the Chinese central government issued a 4 trillion RMB stimulation package in November 2008. In particular, 2.8 trillion RMB of the package were provided by local sovereign offices. Such heavy fiscal burdens were further compounded by the crisis-induced tax shortfalls. To help local offices finance the fiscal stimulus, the central government loosened the restriction on the usage of land revenue for investment activities. Before this action, only a limited number of local authorities were allowed to establish the aforementioned investment units to fund large scale projects. Now most local governments are legally permitted to set up the Local Government Financing Vehicles (LGFVs) to obtain loans from commercial and regulatory banks, in order to finance the infrastructure projects of local governments. As most of these infrastructure projects require inputs of new land spaces, the emergence of such LGFVs boosts the demand in the land market. This mechanism also facilitates credit expansion because the majority of the 2.8 trillion RMB stimulus package is funded via LGFV borrowing. Due to these facts, it is a concern that using the U.S. financial crisis as an exogenous in the land market is no longer appropriate. The credit supply for investors in the land market was not shrinking, but expanding during the financial crisis.[6]

[5] The Chinese central government relaxed this restriction and allowed local sovereigns to issue bonds in 2015 (Gao, Ru, and Tang, 2016).

[6] Ultimately, the credit expansion caused by the fiscal stimulus package would result in price appreciation in the housing market. However, this paper focuses on the crisis impact of year 2008 only. The time length (1.5 months after the issuance of the package) is too short to consider the package's impact on the house market, but is sufficient for the land market.

To this end, another regulatory event is adopted to investigate the impact of credit supply on the land market. The home-purchase restriction order released by central government in 2010 is considered. This restriction order prohibits residential households (who with a registered permanent residence or Hukou) from buying more than two units of residential premises; and non-residential households (who without Hukou) from buying more than one unit of premises with proof of local tax receipts or social security records of 1 year. Furthermore, the restriction order also increases the endowment payment required for mortgage loans issued by commercial banks. It also demands that banks charge a higher interest rate for a second mortgage. It is considered as the strictest housing policy in China and extensively depresses a large fraction of households from home purchasing. The restriction order covers more than 40 cities across China, including first-tier cities such as Shanghai and Beijing, as well as second- or third-tier cities such as Haikou.[7] Therefore, the home-purchase restriction order is a shock to the demand sides of both housing and land markets, and affects prices negatively. The higher standards of mortgage loans also contract the credit supply provided to households.

Under the restriction order, the house (land) price of a province that is more financially liberalised is expected to illustrate a larger drop. Wei, Fang, Gu, and Zhou (2015) suggest that houses are perceived as an alternative investment vehicle for citizens and corporations, because of the incomplete and frictional financial system of China. Due to the strict capital control policy, domestic individuals and corporations cannot freely invest in the overseas capital markets. A Qualified Domestic Institutional Investor (i.e., QDII) is required to make investments in overseas financial markets on behalf of local citizens and firms. All QDIIs are foreign banking institutions. A more financially liberalised province provides a more comprehensive QDII facility, which helps to diversify the capital away from the housing (land) market. Therefore, it is reasonable to argue that the home-purchase restriction order has a more prominent negative effect on the house and land prices of a province that is more financially deregulated. The coefficient scale is larger for the land price than for the house price due to the relative importance of land in China's urban economy.

H3: The home-purchase restriction order affects the house and land prices negatively. Such negative effects are more severe in more financially liberalised provinces. For the same province, the land price depreciates more than the house price under the restriction order.

Land is the foundation for house construction. However, the supply of urban land is highly constrained by the regulations and geographical features of the location. The literature shows that the

[7] The tier systemic was introduced as a ranking system by the Chinese central government in the 1980s to facilitate the staged roll out of infrastructure and urban development throughout the country. Cities were ranked by tier according to the government's development priorities. It is a bureaucratic classification and is also used as a proxy for demographic and social segmentation in China. The first-tier cities are Beijing, Shanghai, Guangzhou, and Shenzhen. The Second-tier cities are provincial capitals and coastal cities, such as Tianjin, Chongqing, Chengdu, Wuhan, and Xiamen. Third and fourth-tier cities are medium-sized cities of each province.

proportion of land that can be used for construction purposes has a direct impact on the elasticity of housing supply. Studies by Gyourko, Saiz, and Summers (2008) and Glaeser and Ward (2009) find that regulations on the land usage right can partially explain the price variations in major U.S. housing markets. Saiz (2010) collects satellite-generated data on the terrain elevation and presence of water areas in the U.S. metropolitan areas to construct a precise measure of land unavailability. The measure captures the proportion of land that is not suitable for construction usage due to exogenous geographic features. The findings suggest that more geographically constrained cities display lower housing supply elasticities with respect to demand side shocks, and have more expensive housing prices.

Due to the data limitation on China's geography, a quasi-geographical constraint measure is constructed to capture the land availability. Similar to Saiz (2010), this study focuses on relatively scarcity of land induced by predetermined geographic features such as oceans, lakes, mountains, and wetlands. In particular, the constrained land area is calculated as a sum of the following components: the area of afforested land, the area of wetlands and the area of agricultural land. The afforested land includes natural forest and man-made forest. The wetlands include natural wetlands such as coasts and seashores, rivers, lakes and marshland, as well as man-made wetlands. The land for agricultural usage is reported from the survey of 2008 and includes garden land, grazing land and pasture land. The unavailable/undeveloped land is the proportion of constrained land area over the administrative area of each province. More geographically constrained provinces are expected to have more expensive house prices and lower house supply elasticities. Furthermore, the high supply inelasticity amplifies the negative effect of credit contraction on the housing market during the U.S. financial crisis.

H4: The house price of a more geographically constrained province is more expensive. When a province is more geographically constrained and more financially liberalised, it suffers greater house price depreciation during the U.S. financial crisis.

5.3 Data and Measures

This section describes the data. It starts with a review of the existing price index of China's real estate market, followed by an elaboration on the nature of the house price index used in this paper. In the end, the construction of various variables is described.

5.3.1 The House Price Index of China

An ideal house price index should capture the accurate price variations of the same or comparable houses over time. A hedonic price regression method is widely used in the literature. It regresses the house sale prices on a series of variables which characterise the property unit, after controlling for the time effect.[8] The issue with this method is that it requires detailed information on the implicit attributes of a transacted housing unit. Moreover, information on the houses' physical conditions may fail to pick up unobserved and time-varying characteristics that are valued by the market, such as the timely-changing preference of house locations. Case and Shiller (1987) propose a repeated sales method that does not require house quality information. Meanwhile, this method demands that the quality of housing units in the sample remains constant over time. The repeated sale method is widely criticised as it wastes a large amount of transaction data. Nevertheless, the units of the repeated transactions may not be representative of the entire housing market. The nascent nature of China's property market means that there are relatively few repeated sales. However, a large amount of data on new home sales is available at province- and city-level. Wu, Deng, and Liu (2014) adopt the hedonic regression method and construct the first multi-city constant-quality house price in China by using transaction data on newly-built homes. Similarly, Wei, Fang, Gu, and Zhou (2015) use a hybrid approach and construct house price indices for 120 large Chinese cities from 2003 to 2013. The price indices are calculated on sequential sales of new homes within the same real estate development project.

Unfortunately, the transaction data sets used in these papers are detailed mortgage loan data provided by major commercial banks in China, which are private information and not publicly available. For this reason, the 'NBS Average Price Index' is used in this study. This average price index is calculated by dividing the total price of houses by the total floor area of transacted areas in a given month/year and a given city/province. The panel data on the total housing transaction value and the total floor spaces of transacted area variables are collected from the China Real Estate Statistical Yearbooks published by the National Bureau of Statistics (NBS) of China. As pointed in Wu, Deng, and Liu (2014); Wei, Fang, Gu, and Zhou (2015) and Wu, Feng, and Li (2015), the simple NBS average price index has several limitations. Firstly, it fails to consider the substantial quality changes in the housing condition over time. For example, the urbanisation process of China has gradually moved the location of newly constructed homes from inner centres of cities towards their outer circle. This feature is overlooked by the NBS average price index. Secondly, the NBS average price index of a province also ignores the within-province heterogeneities in the quality of housing and geographic location. Wu, Deng, and Liu (2014) find that the failure to consider these features leads to the simple average price index being downwardly biased. Nevertheless, the NBS simple average price indices exhibit highly synchronised co-movement with the hybrid price indices constructed in Wei, Fang, Gu, and Zhou (2015) for major Chinese cities. This assures the usage of the NBS average price index for measuring the fundamental fluctuations in the housing market.

The data on land price for each province is collected from the China Land and Resource Almanac. The information gathered includes a) the transaction value of the state-owned land, the usage right

[8]The regression is performed 1) on each time period separately or 2) with the inclusion of a time dummy for the period of sale.

of which is granted by local governments to developers; and b) the total area of such transacted land.[9] The average land price is the transaction value of the granted land divided by the total land area of each province. The unit of both house and land prices is 'Yuan per square metre'. The data frequency is valued by year. The real house (land) price is the nominal house (land) price divided by the Consumer Price Index (CPI). The CPI data is downloaded from the NBS and can be collected from the China Statistic Yearbook.

5.3.2 Other Variables

As discussed in Wu, Feng, and Li (2015), land lease sale is a major source of local government's off-budgetary revenue. A high budget deficit actively motivates the local governor to engage in land sale transactions, which help to cover budget expenditures. We collect the balance sheet information of the local governments from the China Statistic Yearbook for Regional Economy. The deficit level is calculated as the difference between the budgetary expenditure and the budgetary revenue. Then the budget deficit variable is constructed by dividing the deficit level by the budgetary revenue.

Studies show that real estate prices also reflect households' preferences for quality of urban living. Roloack (1982) claims that wage differences across 98 cities can be largely explained by local attributes, such as pollution. The author also finds that differences in local fiscal conditions account for the price variations in the local house market across the metropolitan areas. Berger, Blomquist, and Peter (2008) find similar results in the transition economy, Russia. In China, Huang, Leung, and Qu (2015) and Zheng, Cao, and Kahn (2011) show that there is a significant premium impact of green infrastructure on local house prices. Zheng, Fu, and Liu (2009) and Oates (1969) find positive influences of local public goods on house prices, such as healthcare services and government spending on education. Therefore, three measures that capture the local environmental and fiscal amenities are proposed in this study. They are the SO_2 emission level, the number of medical professionals per resident and the government spending on education. The emissions of SO_2 (sulphur dioxide) into the air are used to measure the environmental attribute of each province. A higher SO_2 emission level indicates the worse air pollution. Poor air quality discourages residential activities due to health considerations. The data on the SO_2 emissions is collected from the City Statistic Yearbook. To capture the social attributes of the local neighbourhood, the number of medical professionals available per resident is used. China has a population of 1.4 billion. Healthcare resources are scarce and expensive. A higher number of professionals available for residents' medical attention indicate a superior public healthcare facility of the province. Another amenity measure is the local government spending on education. Government spending on education, which is funded by taxation income, indicate the efficiency of the local government. Furthermore, a higher education spending enhances potential learning opportunities, cultural and intellectual benefits, and facilitates urban economic

[9] The full name of variable in (a) is called the Price Value of the State-owned Land Use Rights Granted by Province, Autonomous Region and Municipality.

development. Both data sets are collected from the China Statistic Yearbook for Regional Economy.

The study of Wei, Fang, Gu, and Zhou (2015) suggests that China's enormous house price appreciation is accompanied by an impressive growth in household incomes. The average annual real growth rate of households' disposable incomes was as high as 9.0 percent from 2003 to 2013. The expectation of future income growth contributes to explaining the high demands for house and mortgage loans, even with a high mortgage down payment ratio. Hence, data on the disposable income per capita of urban households is collected from the China Statistic Yearbook for Regional Economy. The real disposable income per capita is calculated as the nominal disposable income per capita divided by the CPI.

In addition, the real growth rate of the cost of buildings completed for real estate development is used as an indicator for construction costs. Such data is collected from the China Statistic Yearbook. The unit is Yuan per square metre.

The 5-year real interest rate of deposit is the nominal rate minus the inflation rate.[10] It is used as a proxy for mortgage payment rate. The nominal 5-year deposit rate is set by the People's Bank of China, and it is the same across all provinces. It is important to point out that the commercial banks of China do not enjoy complete freedom for setting the mortgage rates for their borrowers. There is a special mortgage loan format called the Personal Housing Accumulation Fund Loan (PHPFL), the mortgage loan rates of which are set by the central bank and they cannot be altered.[11] Furthermore, the People's Bank of China also sets the base rate of residents' mortgage loans. For these reasons, it is less likely that the interest rate has a significant explanatory power on house price variations.

A large proportion of the state-owned land is bought from farmers. Therefore, the substitution cost of land usage from agriculture to construction is the foregone agricultural productivity generated by the land. Therefore, it is a direct cost paid by the local government. The agriculture GDP per capita is calculated to measure the agricultural productivity. This is the GDP contributed by agriculture divided by the population of each province. The GDP data is collected from the China Statistic Yearbook for Regional Economy. The population data is collected from the Statistics of City and Country Demographic.

The number of foreign banks established in each province by the end of 2006 is used to measure the degree of financial openness. Various studies have shown that the location pattern of foreign banks across China is significantly linked to international trade, income per capita (He and Yeung, 2011), as well as the deregulation process of local currency business (Zhang and Yang, 2007). The year 2006 is set as the cut-off point when foreign banks were granted full access to the Chinese

[10] The inflation rate is growth rate of CPI.

[11] Information on PHPFL: http://www.boc.cn/en/pbservice/pb2/200806/t20080626_1324012.html.

financial market as part of the WTO agreement.[12] Data on the number of foreign banks in each province is from the Almanac of China's Finance and Banking, which includes the representative offices, branches and sub-branches.

The crisis is a dummy variable that equals one in the year of 2008 and zero otherwise. The variable captures the U.S. financial crisis, which was signalled by the default of Lehman Brothers on 15 September 2008.

The Restriction Regulation is a dummy that is equal to one in the year of 2010 and zero otherwise. It marks the year when China's central government released the notice proposing a home-purchase restriction order. The purpose of this order is to depress the overheating real estate market by imposing restrictions on the purchasing power.

5.4 Empirical Framework and Regression Results

This section explores the impact of financial deregulation on China's house and land prices. It introduces the empirical framework used in this chapter and describes the main regression specification. It is followed by the discussion of the empirical results.

The empirical framework adopted in this study is the panel regression. Since the U.S. financial crisis constitutes an economy-wide exogenous shock, the empirical framework aims to isolate its effect on house price movements by studying differential crisis performance changes across different provinces. The differential crisis performance is linked to the degree of financial openness of a specific province prior to the financial crisis. The empirical strategy assumes that provinces that were more financially open prior to the crisis were more sensitive to the shocks from the global financial crisis. These provinces illustrated larger price depreciations in the real estate and land markets during the crisis period. The degree of financial openness of a province is measured by the number of foreign banking institutions established locally by the end of 2006, which includes foreign bank representative offices, sub-branches and branches.

The dependent variable of the equation (5.1) is the annual real growth rate of the average house prices of the 31 provinces in China. The growth rate is measured as the changes in the logarithms of real house prices. The explanatory variables in the regression include several categories. The 1-year lagged annual growth rate of real land price is used to study the contribution of land towards house price movement. The 1-year lagged change in the local budget deficit ratio is also included to investigate the impact of the local fiscal condition, alternatively known as the sovereign risk, on the real estate market. The lagged observations are considered to explore the causal relationship between

[12] http://www.cbrc.gov.cn/EngdocView.do?docID=2871.

the house price and the two factors, especially when the housing market is a long-term investment. For the demand side, the regional environment amenity and household income are controlled in the regression. The environmental attribute is measured as the annual changes in the logarithms of the SO_2 emissions per square metre. The variable for the wage condition of local households is the annual growth rate of real disposable income per capita. The annual growth rate of real construction costs represents the cost condition of the supply side of the real estate market. The annual real growth of the 5-year interest rate is used as an approximation of the mortgage rate. All of the growth rates mentioned above are calculated as changes in the logarithms of the corresponding measures. The variables of interest are the number of foreign banking institutions established in a province by the end of 2006, the financial crisis dummy, and the interaction term between the two.

$$\begin{aligned}\Delta ln\ house\ price_{i,t} = \alpha_i &+ \beta_i^1 \Delta ln\ land\ price_{i,t-1} + \beta_i^2 \Delta budget\ deficit_{i,t-1} + \beta_i^3 \Delta ln\ SO_{2i,t} \\ &+ \beta_i^4 \Delta ln\ income\ per\ capita_{i,t} + \beta_i^5 \Delta ln\ construction\ cost_{i,t} \\ &+ \beta^6 \Delta 5\ year\ interest\ rate_t + \gamma_i foreign\ banks\ 2006_i \\ &+ \sigma crisis_t + \eta_i foreign\ banks\ 2006_i * crisis_t + \epsilon_{i,t}\end{aligned} \tag{5.1}$$

Table 5.1 provides the description of the regression results of equation (5.1). The first column of Table 5.1 is a simple panel regression with heteroskedasticity-consistent standard errors. Column 2 reports the coefficients for the same regression with control for the year effect. Column 3 of Table 5.1 is the result when both the year and fixed effects are included in the panel regression. Each regression includes the interaction term between the crisis dummy of the year 2008 and the degree of financial openness prior to the crisis. The regression allows for differential linear time trends by province. Standard errors are corrected to allow clustering of the error terms at the provincial level.

The findings in Table 5.1 confirm the hypothesis that a more financially open province experiences more severe price depreciation of its housing market during the financial crisis. On average, the real house price declines by an additional 0.5 percentage points during the financial crisis for a province that is at the 75^{th} percentile of the pre-crisis financial openness distribution, compared to a province that is at the 25^{th} percentile of that distribution.[13] The interaction term has statistical significance at 1 percentage level, and remains significant after controlling for the fixed effect and year effect. For economic significance, 1 standard deviation increase in the bank presence would intensify the house price depreciation in that province by 6 percentage points during financial crisis.[14] As expected, the financial crisis dummy has a significant negative impact on the house prices across the 31 provinces in China. That is, the global financial turmoil originating from the U.S. sub-mortgage crisis generates a contagious damage to the Chinese real estate market. The real house prices of China decrease by 7.29 percentage points during the financial crisis on average, which is significant at 1 percentage level. However, this impact of the financial crisis diminishes after controlling for the fixed effect.

[13] The pre-crisis financial openness distribution is 12 at the 75^{th} percentile compared to 0 at the 25^{th} percentile.

[14] For economic significance, we calculate as standard deviation of independent variable times coefficient divided by the standard deviation of the dependent variable.

The coefficient of the foreign bank 2006 variable suggests that financial deregulation indeed boosts the real estate market development of each province. The establishment of an additional foreign bank in a province would enhance the local property price growth by 0.01 percent, in comparison to a province with no foreign banks. The economic significance of the foreign banks, which is 4.45 percentage appreciation in the house price for one standard deviation increase in the foreign banks by the end of 2006. The small scale of the coefficient is reasonable given the fact that foreign banks only represent a small portion of the banking sector assets in China. According to the annual report published by CBRC (2008), the total assets of foreign banks by the end of 2007 were RMB 1253 billion, accounting for 2.38% of China's total banking assets.

Turning to other determinants of house prices, a few interesting results emerge from the regressions. An increase in the previous year's land price positively contributes to higher house price growth. The scale of the coefficients is 1.62 percentage points, when the year and fixed effects are controlled. Although the cost of obtaining land usage right is the primary cost for real estate developers, the influence of the previous year's land transaction price on local house prices is marginally significant. On the other hand, the fiscal condition of the local government has a significant impact on house prices. A one percentage point rise in the previous year's budget deficit ratio of the province's sovereign leads to a 2.9 percentage points increase in the property price (column 1 of Table 5.1), at 1 percent significant level. The coefficient remains at a similar economic scale when the year and fixed effects are controlled, at 5 percent significance. For the demand side, a higher SO_2 emission significantly discourages the price growth of the local property market. The negative sign of the environment amenity variable supports the findings in the literature (e.g., Wu, Feng, and Li, 2015; Huang, Leung, and Qu, 2015; Zheng, Cao, and Kahn, 2011) that households value local amenities and are willing to pay more for better quality. Severe air pollution (i.e., a higher level of SO_2 emission) negatively affects the house price. Wei, Fang, Gu, and Zhou (2015) suggest that there is a strong link between the rapid growth of China's housing market and households' income growth. Our finding indicates that the higher disposable income of the local citizens has a positive influence on the house price growth. However, the coefficients are not statistically significant. Moving onto the supply side of a property market, the construction cost paid by the real estate developers significantly increases the house transaction price. A one percentage point rise in the real construction cost pushes up the real house price by 10.16 percentage points (column 1 of Table 5.1). The long-term interest rate does not seem to have a significant impact on house price growth. This could be caused by the inflexible pricing system of China's mortgage market, as discussed in section 5.3. Overall, the model explains 27.33 percent of variations in the house price movement in China.

As land is also a tradable asset, this study also investigates the impact of financial deregulation on the land price. A similar set-up as equation (5.1) is adopted by performing the panel regressions on the annual growth rate of the real land price across the 31 provinces in China. For the regressors, the changes in the previous year's budget deficit ratios of the local government is used. This captures the financial conditions of the suppliers in the land market. The real construction cost growth rate of real estate developers is linked to the demand side of the land market. The variables of interest are the number of foreign banking institutions established in a province by the end of 2006, the financial crisis dummy, and the interaction term between the two. Another motivation for studying the land price is to compare its reaction to financial deregulation with the reaction of the house market. For this reason, all other variables are kept to make the model more comparable with equation (5.1), including the annual growth rates of SO_2 emissions per square metre, the annual growth rate of real income per capita, and the annual growth rate of the real 5-year interest rate. The regression specification of land price is as equation (5.2).

$$\begin{aligned}\Delta ln\ land\ price_{i,t} = \alpha_i &+ \beta_i^1 \Delta budget\ deficit_{i,t-1} + \beta_i^2 \Delta ln\ SO_{2i,t} \\ &+ \beta_i^3 \Delta ln\ income\ per\ capita_{i,t} + \beta_i^4 \Delta ln\ construction\ cost_{i,t} \\ &+ \beta^5 \Delta 5\ year\ interest\ rate_t + \gamma_i foreign\ banks\ 2006_i \\ &+ \sigma crisis_t + \eta_i foreign\ banks\ 2006 * crisis_t + \epsilon_{i,t}\end{aligned} \tag{5.2}$$

Table 5.2 reports the regression coefficients of equation (5.2). Column 1 is a standard panel regression with heteroskedasticity-consistent standard errors. The year effect and fixed effect are included gradually in the regression. The results are reported in column 2 and column 3 respectively. Standard errors are corrected to allow clustering of the error terms at the provincial level.

The results of Table 5.2 indicate that financial deregulation has a much larger economic impact on the land price than on the house price of the same province. The positive sign of coefficients of the financial openness variable confirms the hypothesis that financial liberalisation contributes to land market development, with statistical and economic significance. In particular, the establishment of one additional foreign bank in a province increases the local land price by 0.11 percentage points. Compared to the 0.01 percentage increase in the local house price, the credit expansion tends to have a premium influence on the regional land market development.[15] Such a superior reaction of the land price highlights the relative importance of the land market. This aligns with the existing theory that land is highly inelastic and is a fundamental cost of real estate (e.g., Kiyotaki, Michaelides, and Nikolov, 2011; Wu, Gyourko, and Deng, 2016; Ghent and Owyang, 2010). After controlling for the year and fixed effects, the financial crisis has a significant negative effect on the land price, whose coefficient is as high as 22.25 percentage points. However, such coefficients of the financial crisis are not consistent with the other two model set-ups. Therefore, it is undetermined how the financial crisis impacts the land market. Nevertheless, the interaction term between the financial openness and the crisis dummy has no statistical significance across all three model set-ups. One potential explanation of such an ambiguous impact of the financial crisis on the land price is because of China's 4 trillion RMB stimulus package in 2008. This stimulation plan was issued by the central

[15] Economically, one standard deviation increase in the number of foreign banks at the end of 2006 would increase the local land market by 4.61 percentage points, whereas increasing the local house market by 0.41 percentage points.

government of China in November 2008, right after the explosion of the U.S. financial crisis. A total of 2.8 trillion RMB was supplied by the local governments of each province. In order to generate sufficient funds to fulfil this fiscal stimulus plan, local sovereigns became heavily engaged with the land lease sales activity. As the quantity of land available for sale is highly constrained by the regulation and geographic conditions of each province, local governments tend to increase the sale price to boost their revenue. In addition, in the end of 2008, the central government issued the first legal document that allowed most local authorities to use the proceeds of land lease sales to fund investment activity. This action boosts the emergence of the LGFVs, which is an investment unit created by local government to obtain loans from banks to fund the fiscal stimulus. The primary destination of this capital is the land market as construction and infrastructure projects require the usage right of state-owned land. Ultimately, expansion of cheap credit funded by LGFVs facilitates the land market growth in the post-crisis period. This is why we observe the sharp land price increase during 2008 and 2010 in Figure (5.1).

In order to systematically assess the impacts of financial liberalisation on the house and land markets, another event in China's real estate development process is used. On 17th April 2010, the Chinese State Council issued the 'Notice of the State Council on Resolutely Curbing the Soaring House Prices in Certain Cities'.[16] This notice demanded that all regional and relevant departments effectively performed the duties of stabilising the housing market. Immediately, various cities' governments issued real estate policies that imposed direct restrictions on households' home purchase actions. For example, Beijing was the first city to release a restriction order, which limited households with a Beijing local Hukou to a maximum of two home properties, and prohibited any Non-Hukou households from any potential purchases of house in Beijing. The restriction policies issued by individual city's governments are endogenously linked to the local house market developments. Therefore, the year when the state council's notice was released is adopted as the event of interest because the central government's action was largely unexpected by the investors and households.

It is crucial to point out that the event of the U.S. financial crisis impacts both the supply and demand sides of the real estate markets, while the event of the restriction order has a dominant impact on the demand side. The home purchase restriction order discourages households from home purchasing by posing requirements on the legal status of a household's residence. It also has a negative influence on the credit market by raising the requirements for mortgage loans. For example, a 50 percent down payment rate is demanded for a second mortgage loan. This changes the interpretation of the financial deregulation's impact on the house and land markets. The financial deregulation improves the investment facility of a province by offering access to overseas capital markets. In China, individuals are not legally allowed to invest in overseas capital market. Individual residents and corporations are required to rely on a Qualified Domestic Institutional Investor (i.e., QDII) to make investments on their behalf. All QDII are foreign banking institutions and asset management

[16] http://www.gov.cn/zwgk/2010-04/17/content_1584927.htm.

firms.[17] Therefore, a more financially liberalised province enjoys a superior QDII facility, and provides efficient and effective access to overseas capital markets. Under the restriction order, investors opt for alternative investment products, such as foreign currency or foreign stock markets, instead of the residential property and land markets. An efficient QDII facility diversifies the capital flows from the local real estate and land markets to the corresponding financial sector, helping to stabilise the prices. Therefore, the property (land) price is expected to depreciate more in a more financially open province, under the home-restriction order.

The results for the regressions of house and land prices on the home purchase restriction order are reported in Table 5.3 and Table 5.4 respectively. The model specification is akin to the equation (5.1) for the house price, and equation (5.2) for the land price. The results suggest that the release of the restriction order negatively affects the house and land prices across all provinces. It is interesting that the restriction order has a larger influence on the land price than the house price, despite the fact that the property market is the primary target of such a restriction order. Under the restriction order, the house price depreciates by 2.74 percentage points on average, while the land price depreciates by 44.73 percentage points, after controlling for the year and fixed effects. Statistically, the impact on the land price is more significant than that on the house price. Table 5.3 shows that, after the restriction order is announced, the real house price declines on average by an additional 0.72 percentage points for a province that is at the 75^{th} percentile of the pre-crisis financial openness distribution, compared to a province that is at the 25^{th} percentile of that distribution, after controlling for the year and fixed effects.[18] This impact is statistically significant at 1 percentage level. Turning to Table 5.4, the land price observes a similar mediation effect of financial openness on the home purchase restriction order, but with less significance level of 5 percent. This is because the real estate market is widely perceived as an investment option in China by local citizens, especially when the economy enjoys high household savings. However, this is not the case for the land market since the governments are the monopoly suppliers of urban land. The results of the financial liberalisation are consistent with previous findings on equation (5.1) and equation (5.2). The financial liberalisation has a larger impact on the land price (as shown in Table 5.4) than that on the house price (as shown in Table 5.3). With one additional establishment of a foreign bank in a province, the land price appreciates by 0.14 percent, while the house price appreciates by 0.03 percent. The results confirm hypothesis 2 that land price illustrates a premium reaction towards financial deregulation in comparison to the reaction of the house price.

Table 5.5 and 5.6 investigate the influence of unavailable land on the cross-sectional house price movements.[19] Table 5.5 interacts the proportion of unavailable land and the financial crisis. The study by Saiz (2010) suggests that areas that have a larger portion of unavailable land (that cannot

[17]Name list and regulatory requirement published by the China Securities Regulatory Commission: http://www.csrc.gov.cn/pub/newsite/gjb/sczr/qfiiylb/.

[18]Pre-crisis financial openness distribution is 12 at the 75^{th} percentile compared to 0 at the 25^{th} percentile.

[19]The relationship between the unavailable land and the land price is not studied in this project.

be used for construction and real estate purposes) exhibit higher housing supply inelasticity. The house prices in these areas are more expensive. In Table 5.5, the coefficients of the unavailable land, under three different empirical settings, are positive and statistically significant. The findings are aligned with Saiz (2010) that a more geographic constrained city experiences higher house price. The interaction term between the financial crisis and the unavailable land shows consistent negative and significant impact on the cross-sectional house prices. It suggests that the geographic constraint would intensify the negative shock of the financial crisis in the Chinese property market. Furthermore, the economic scale of this interaction term is also significant. After controlling the year and fixed effects, the house price of a province that is more geographically constrained with 1 standard deviation less land available experience a larger house price drop during the financial crisis, by 86.23 percentage points. The findings in Table 5.5 indicate that geography indeed impacts on the property market. The next hypothesis to investigate is that whether the geographical constraint condition of a province, which is measured as the unavailable land, is expected to intensify the impact of financial deregulation on house prices during the crisis period. A triple interaction term among the number of foreign banks by the end of 2006, the financial crisis dummy and the proportion of unavailable land for each province, is constructed and included in Table 5.6. We expect the triple interaction term to have a negative coefficient. The findings in Table 5.6 indicate that a more geographically constrained province has a higher house price with statistical and economic significance. A one percentage increase in the proportion of unavailable land lifts the local house price by 4.51 percentage points at 1 percent significant level, after controlling for the year and fixed effects. In addition, the triple interaction term illustrates a significant and negative coefficient. Economically, it implies that with one standard deviation increase in the land unavailability, the house price experiences additional 1 percentage depreciation in a province that is at the 75^{th} percentile of the pre-crisis financial openness distribution, compared to a province that is at 25^{th} percentile of that distribution.

5.4.1 Robustness Regression

To ensure that our results are consistent, several robustness tests are performed. First, the literature shows that economic productivity is a main factor that determines house prices. For this reason, all of the regressions reported in this study are performed with an additional variable, the real growth rate of GDP per capita for the 31 provinces of China. The regression findings remain consistent. Furthermore, the productivity variable illustrates a positive and significant impact on house price movement. However, this productivity measure is highly correlated with the construction cost and households' income.[20] The second robustness check conducted considers the substitutional cost of using land for construction instead of traditional farming. The agricultural GDP generated by the land is foregone. Therefore, the annual growth of real agriculture GDP per capita is included in the regression. Furthermore, this robust regression also considers the impact of local fiscal and cultural amenities on the property market. Two additional demand side variables of local healthcare facility

[20]The results with the inclusion of productivity are available on request.

and public amenity are included. They are the number of medical persons per resident and the real growth rate of local government expenditure on education. The robust regression results are reported in Table 5.7. The findings stay consistent. Table 5.7 suggests that a higher substitutional cost of land (higher agricultural GDP foregone by using the land for construction) increases the real house price. In addition, households are willing to pay more to enjoy a higher quality of urban life, with a superior healthcare system and a more efficient local government.

Thirdly, alternative measures of financial openness are used for the robustness test. The number of foreign banking institutions at the end of year 2006 is divided into two separate measures: the number of foreign bank branches and the number of foreign bank representative offices. The findings on financial deregulation are not altered. A time varying financial openness variable is calculated. This measures the number of foreign banking institutions established in the province of each year, instead of by the end of 2006. Despite that this measure would introduce a potential endogenous issue, the results remain robust.

5.5 Conclusion

This chapter studies a causal relationship between credit supply and the house (land) price. It focuses on the financial deregulation process of China in opening up its local currency business to foreign banks. The entrance of foreign banks expands the credit supply to local residents and corporations. The results show that this expansion in the credit supply contributes to the price appreciation in the local property (land) market across the 31 provinces. The empirical investigation is conducted via two exogenous shocks. Firstly, the U.S. financial crisis is identified as an exogenous drop in the household credit in China. This is because foreign banks reduce credit lending to domestic customers. Variation in the exposure to this drop is used as the identification strategy to study the impact of supply of household credit on property price. The results show that the housing market of a more financially liberalised province experiences more severe price depreciation during the financial crisis. Secondly, under a home purchase restriction order issued by the central government, both house and land prices depreciate. This price depreciation is more severe in a more financially liberalised province, which offers a more efficient overseas investment facility. The third important finding of this study is that land price illustrates a superior reaction to credit expansion than the house price of the same province. Furthermore, this relatively stronger reaction of the land price over the property price is observed in various settings explored in this chapter. It is, therefore, essential to realise the relative importance of the land market towards urban economic development. Finally, the impact of geographical constraints on house prices is explored. The findings suggest that higher house prices are observed in more geographically constrained provinces. Furthermore, the house prices depreciate more during the financial crisis in provinces that are more geographically constrained, and more financially deregulated. Various robustness checks are also conducted to support the findings.

The data used in this project is a simple average house price index across the 31 provinces, issued by the NBS of China. This price index has been widely criticised for several limitations. For example, it fails to capture the quality of houses that changes with time. It is important to construct a relatively accurate house price index with more comprehensive house transaction data, such as the one used in Wei, Fang, Gu, and Zhou (2015). It is also important to search and collect direct information on the credit loans provided foreign banks in each province (if possible). Besides, it is also essential to study the impact of geographical constraints on the land transaction prices. More theoretical engagement will be placed on the relationship between land supply elasticity and house prices, in order to study the extent to which land prices influence house prices. Furthermore, the influence of public finance is also worthy of investigation.

Figure 5.1. Real House and Land Prices

This figure depicts the logarithms of annual average real house and land prices across 31 provinces of China. The house price data is based on the annual average real residential house prices of 31 provinces, published by the National Bureau of Statistics of China. The land price is based on information provided in the China Land and Resource Almanac. The sample period ranges from 1999 to 2014. The unit is Yuan per square metre. The first vertical line marks the U.S. Subprime Crisis in 2007. The second vertical line marks the release of the House Purchase Restriction Order by the central government of China in 2010.

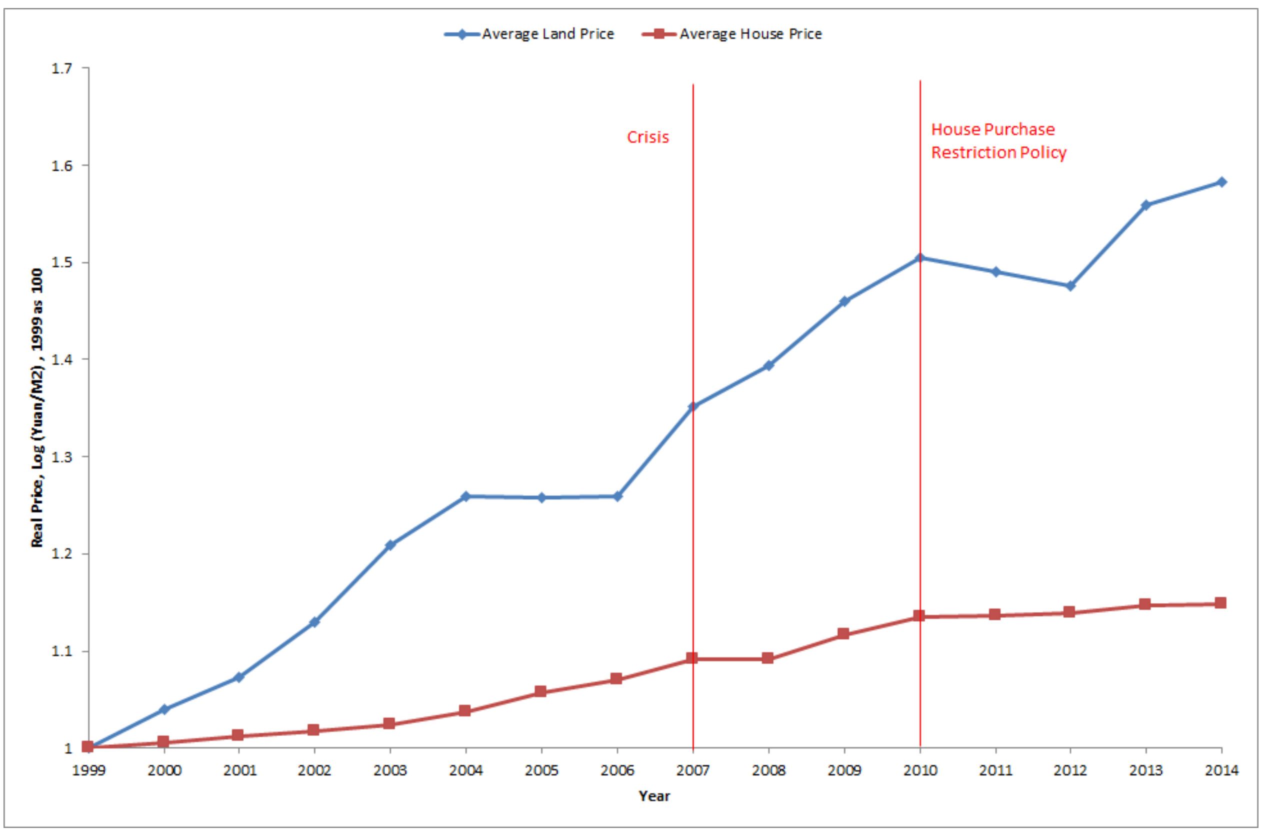


Figure 5.2. Real Land Price

This figure displays the annual average real land price from 1999 to 2014 across 31 provinces of China, together with the real land prices for Beijing and Gangsu. Beijing (Gangsu) is the municipal city that experienced the highest (lowest) land price appreciation during the sample period. The unit is Yuan per square metre. The first vertical line marks the U.S. Subprime Crisis in 2007. The second vertical line marks the release of the House Purchase Restriction Order by the central government of China in 2010. The value label for Beijing's land price is on the right.

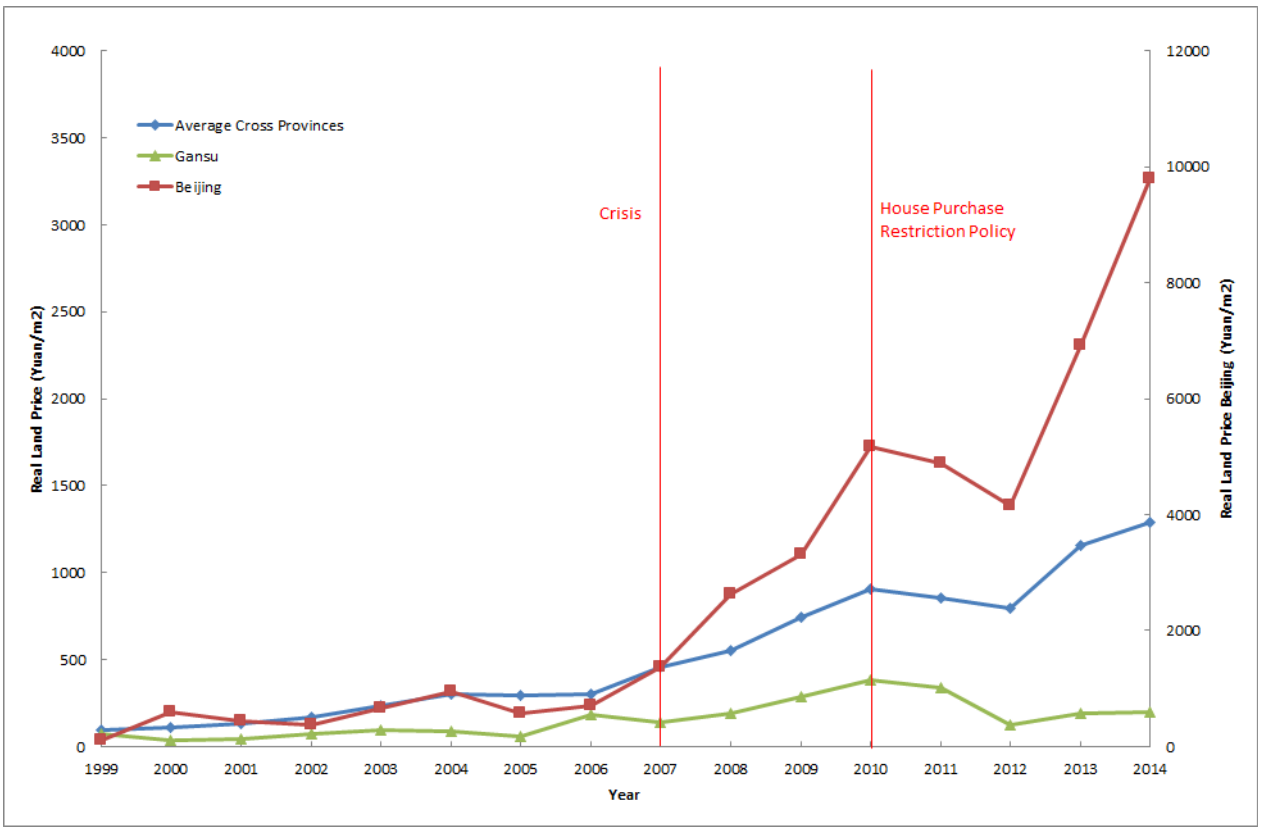


Figure 5.3. Foreign Banking Institutions in China: 1980-2006

This figure depicts the total number of foreign financial institutions, and the new entry of foreign financial institutions in China from 1980 to 2006. The source of figure is from the China Society for Finance and Banking (CBRC, 2007; He and Yeung, 2011).

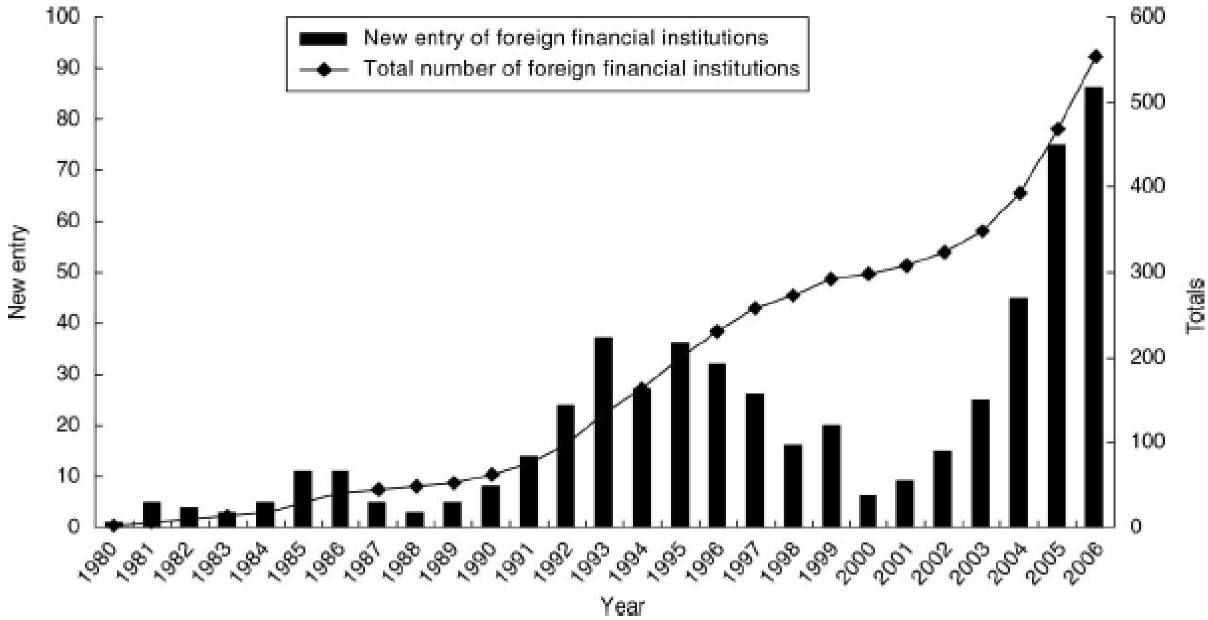


Figure 5.4. Location Distribution of Foreign Banking Institutions in China, 2006

This figure depicts the location distribution of foreign banks, including representative offices and branches, in China by the end of 2006. The source of figure is from He and Yeung (2011).

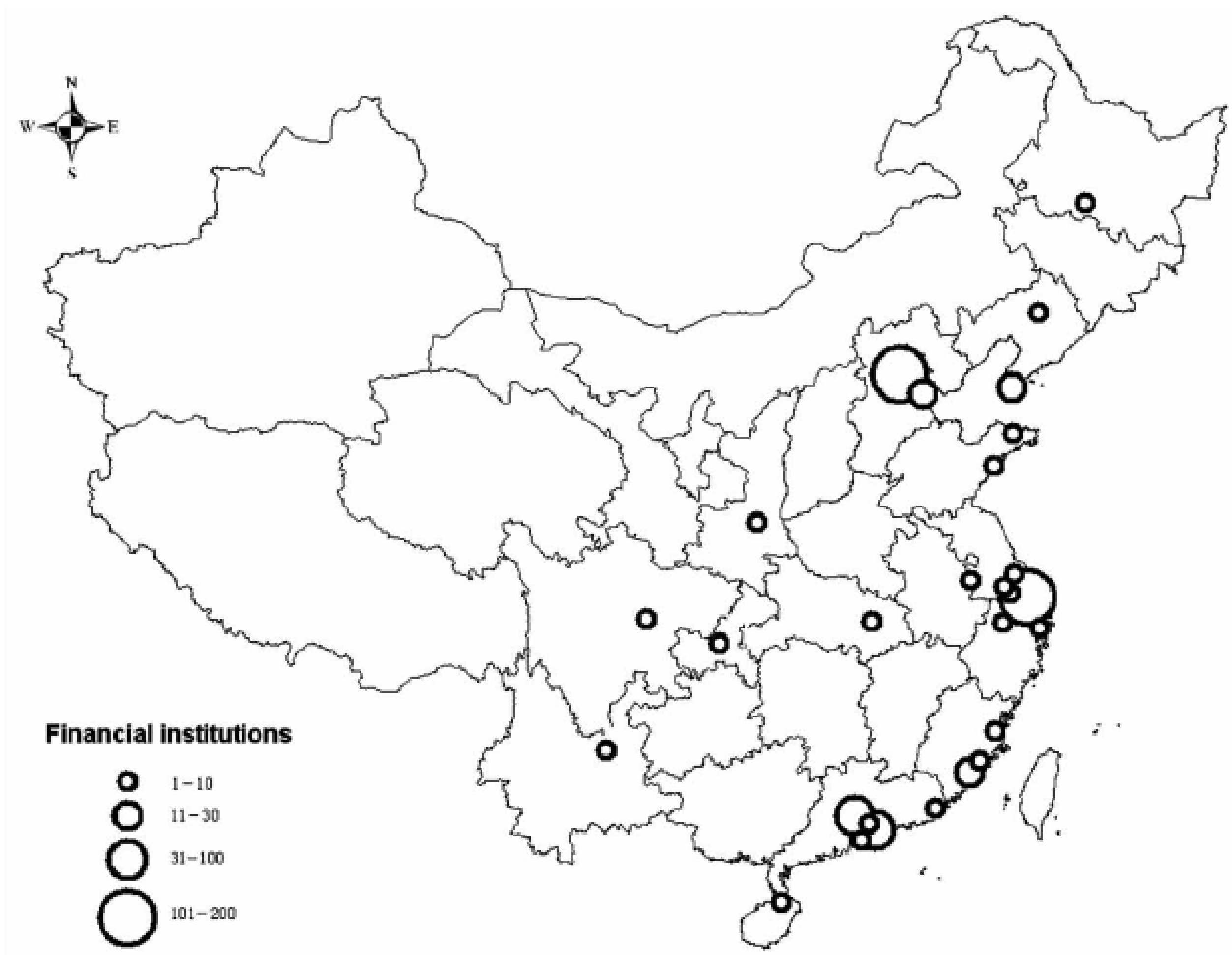


Table 5.1. Regression of Real House Price

The following table reports the panel regressions of the annual growth rate of real house prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual growth rate of real land price (1-year lag), annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the financial crisis dummy and the interaction between the number of foreign banks at the end of 2006 and the financial crisis dummy. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln house price			
Δln land price (lagged)	0.0090	0.0153*	0.0162**
Δbudget deficit (lagged)	0.0289***	0.0240**	0.0277**
Δln SO2	-0.0185*	-0.0429**	-0.0442**
Δln income per capita	0.0601	0.0611	0.0578
Δln construction cost	0.1436***	0.1023***	0.1016***
Δ5-year interest rate	-0.0000***	0.0000	0.0000
Foreign banks 2006	0.0001***	0.0001**	-
Crisis	-0.0729***	-0.0949***	-0.0161
Foreign banks 2006*Crisis	-0.0004**	-0.0005***	-0.0005***
Constant	0.0677***	0.0890***	0.0122
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.1166	0.2756	0.2733
N	372	372	372

Table 5.2. Regression of Real Land Price

The following table reports the panel regressions of the annual growth rate of real land prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the financial crisis dummy and the interaction between the number of foreign banks at the end of 2006 and the financial crisis dummy. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln land price			
Δbudget deficit (lagged)	0.1229**	0.0579	0.0544
Δln SO2	0.0305	0.0270	0.0414
Δln income per capita	-0.3929***	0.0557	0.0106
Δln construction cost	0.3397	0.2598	0.2413
Δ5-year interest rate	-0.0000**	0.0000	0.0000**
Foreign banks 2006	0.0011***	0.0010***	-
Crisis	0.0121	-0.0531	-0.2225**
Foreign banks 2006*Crisis	0.0006	0.0006	0.0006
Constant	0.1170***	0.1531**	0.3450***
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.0483	0.1824	0.1691
N	372	372	372

Table 5.3. Regression of Real House Price: Restriction Regulation

The following table reports the panel regressions of the annual growth rate of real house prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual growth rate of real land price (1-year lag), annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the restriction regulation dummy, and the interaction between the number of foreign banks at the end of 2006 and the restriction order dummy. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln house price			
Δln land price (lagged)	0.0006	0.0233***	0.0242***
Δbudget deficit (lagged)	0.0366***	0.0311***	0.0347***
Δln SO2	-0.0115	-0.0387*	-0.0392*
Δln income per capita	0.0130	0.1255	0.1182
Δln construction cost	0.1301***	0.0884**	0.0868**
Δ5-year interest rate	-0.0000**	-0.0000**	-0.0000
Foreign banks 2006	0.0003***	0.0003***	-
Restriction Regulation	-0.0260***	-0.0835***	-0.0274*
Foreign banks 2006*Restriction Regulation	-0.0005***	-0.0006***	-0.0006***
Constant	0.0793***	0.0897***	0.0001
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.0968	0.3042	0.2899
N	372	372	372

Table 5.4. Regression of Real Land Price: Restriction Regulation

The following table reports the panel regressions of the annual growth rate of real land prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the restriction regulation dummy, and the interaction between the number of foreign banks at the end of 2006 and the restriction order dummy. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln land price			
Δbudget deficit (lagged)	0.1180**	0.0580	0.0546
Δln SO2	-0.0013	0.0257	0.0399
Δln income per capita	-0.5848***	0.0910	0.0495
Δln construction cost	0.3093	0.2516	0.2335
Δ5-year interest rate	0.0000	0.0000	0.0000*
Foreign banks 2006	0.0014***	0.0013***	-
Restriction Regulation	-0.1373***	-0.1592**	-0.4473***
Foreign banks 2006*Restriction Regulation	-0.0005	-0.0007**	-0.0007**
Constant	0.1868***	0.1463**	0.3421***
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.0818	0.1834	0.1610
N	372	372	372

Table 5.5. Regression of Real House Price: Land Availability

The following table reports the panel regressions of the annual growth rate of real house prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual growth rate of real land price (1-year lag), annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the financial crisis dummy, the proportion of unavailable land of a province, and the interaction term between the financial crisis and the unavailable land. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln house price			
Δln land price (lagged)	0.0096	0.0151*	0.0184**
Δbudget deficit (lagged)	0.0289***	0.0242**	0.0284***
Δln SO2	-0.0187*	-0.0431**	-0.0443**
Δln income per capita	0.0608	0.0398	0.0425
Δln construction cost	0.1421***	0.1015***	0.0739**
Δ5-year interest rate	-0.0000***	0.0000	0.0000
Crisis	-0.5585**	-0.6630***	-0.4424*
Unavailable land	0.1818***	0.1544**	4.5479***
Crisis*Unavailable land	-0.4843*	-0.5986**	-0.4410*
Constant	0.2493***	0.2138***	-4.4917***
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.1157	0.2734	0.0285
N	370	370	370

Table 5.6. Regression of Real House Price: Land Availability (Continue)

The following table reports the panel regressions of the annual growth rate of real house prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual growth rate of real land price (1-year lag), annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the financial crisis dummy, the proportion of unavailable land of a province, and a triple interaction term among the number of foreign banks, the financial crisis and the unavailable land. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln house price			
Δln land price (lagged)	0.0099	0.0155*	0.0187**
Δbudget deficit (lagged)	0.0288***	0.0243**	0.0284***
Δln SO2	-0.0188*	-0.0430**	-0.0443**
Δln income per capita	0.0597	0.0455	0.0408
Δln construction cost	0.1425***	0.1026***	0.0754**
Δ5-year interest rate	-0.0000***	0.0000	0.0000
Foreign banks 2006	0.0001	0.0001	-
Crisis	-0.0723***	-0.0942***	-0.0007
Unavailable land	-0.0061	0.0263**	4.5055***
Foreign banks 2006*Crisis*Unavailable land	-0.0005**	-0.0006***	-0.0004**
Constant	0.0736	0.1163	-4.4499***
Year Effect	No	Yes	Yes
Fixed Effect	No	No	Yes
R^2 Overall	0.1179	0.2752	0.0293
N	372	372	372

Table 5.7. Robust Regression of Real House Price

The following table reports the panel regressions of the annual growth rate of real house prices for 31 provinces of China from 1999 to 2014. Explanatory variables include annual growth rate of real land price (1-year lag), annual changes in the government budget deficit ratio (1-year lag), annual growth rate of SO_2 emissions, annual growth rate of real disposable income per capita, annual growth rate of real construction costs, annual growth rate of 5-year real interest rate, the number of foreign banks established at the end of 2006, the financial crisis dummy and the interaction between the number of foreign banks at the end of 2006 and the financial crisis dummy. Additional robust control variables are the annual changes in the medical personnel per resident, the annual growth rate of government spending on education, and the annual growth rate of real agriculture GDP per capita. All regressions are clustered at the province level. Year and fixed effects are included accordingly in the regression. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

Dependent variable: Δln house price			
Δln land price (lagged)	0.0142	0.0145	0.0156*
Δbudget deficit (lagged)	0.0272***	0.0318***	0.0277**
Δln SO2	-0.0187**	-0.0204**	-0.0369**
Δln income per capita	0.0869**	0.0808**	0.0132
Δln construction cost	0.1311***	0.1286***	0.0899***
Δ5-year interest rate	0.6127***	0.6581***	1.4840**
Foreign banks 2006	0.0002***	-	-
Crisis	-0.0551***	-0.0530***	-0.0123
Foreign banks 2006*Crisis	-0.0004**	-0.0004**	-0.0004**
ΔMedicalPerson/Population	-11.4002	-16.5759	-17.0158
Δln Education	0.0525***	0.0512**	-0.0020
Δln farming GDP per capital	0.1785***	0.2387***	0.0861
Constant	0.0479***	0.0492***	0.0444**
Year Effect	No	No	Yes
Fixed Effect	No	Yes	Yes
R^2 Overall	0.1830	0.1714	0.2925
N	372	372	372

Chapter 6

Conclusion

This thesis provides evidence of the importance of media content on credit risk. In Chapter 2, we explore the impact of the government bailout policies on sector-wide systemic risk. A new systemic risk measure is proposed in this study, which is the price difference between a basket of single-name CDSs on individual firms, versus a CDS index that constitutes the same underlying names as the basket. We provide theoretical and empirical evidence that such a measure is highly linked to various systemic risk measures suggested in the literature, such as the autocorrelation coefficient, the principal components of cross sectional stock returns, the aggregate counterparty risk, and the implied correlation. We give this measure a term 'basket-index spread'. We find that this spread moves into negative territory during the financial crisis, and reacts positively to affirmative government bailout news. During the financial crisis, the demand for crash insurance products, such as the CDS index, increases due to risk-averse investors worrying about the potential market collapse. Therefore, the market price of the CDS index, which reflects such expectations of future joint default scenarios, increases due to the higher demand. As a result, the basket-index spread declines. When the government takes bailout action to save the market, it shifts the systemic risk away, which reduces the price of the CDS index, leading to an increase in the basket-index spread. To construct the news variable, we apply the bag-of-words analysis algorithm on the news articles published on the ECB and IMF websites, with a comprehensive corpus and lexicon on political debate and financial opinions. A sentiment score is constructed. A positive score indicates active engagement of governments and authorities in rescuing the financial (and sovereign bonds) sector, while a negative score suggests the reluctance of authorities to bailout the failing market. The findings suggest that the systemic risk reacts to government bailout news with high levels of economic and statistical significance. Furthermore, bailout actions conducted by the ECB have a dominant impact on the financial and sovereign sectors' systemic risk, whereas the IMF interventions affect the non-financial sector. We also find that the negative basket-index spread favours a systemic risk story over a liquidity risk story. Robustness tests suggest that the spread measure has a significant predicting power on the option risk reversal and cross sectional equity returns.

It is worthwhile investigating whether such a systemic risk measure can be applied to the credit markets of different geographic locations. For example, it would be very tempting to use the iTraxx CDX to capture the systemic risk in the U.S. market during the past financial crisis. In addition, by using two basket-index spreads for the financial and sovereign sectors, future research work will be able to explore 1) the amount of systemic risk that is transferred between the financial and sovereign sectors via various bailout actions, 2) the moneyness of a government put protection on the financial sector. Moreover, our study shows that the ECB news impacts the financial and sovereign sectors, while the IMF news only impacts the non-financial sector. It is necessary to conduct further investigations on the underlying causes for such differences. For example, more advanced linguistic analysis could be applied on the policies' contents for both resources, in order to decide whether there is any pattern in the market reaction to the news issued by the ECB (or the IMF). Relevant policy applications can be developed to improve the regulation communication (i.e., design the wording of policies to improve the effectiveness). Besides, since the bail-in by a government has been considered as a default action by the ISDA, future researches should focus on, firstly, investigating how the change will impact the standard credit risk pricing model, especially on the recovery rate. The companies with the bail-in led defaults should have better recovery rates, thanks to the capital injected by the government. The simply intensity-based model illustrated in the appendix could be a start. Secondly, will such a change reduce the effectiveness and efficiency of future government crisis interventions on the financial market? Will a future government bailout action cause any collateral damages in the credit market? Will it help to reduce the moral hazard in the CDS market? We hope to pursue these questions in future research.

In Chapter 3, we study the impact of sentiment on the sovereign credit risk. We adopt a much advanced sentiment data-set, which is the Thomson Reuters News Analytics (TRNA) database. The TRNA overcomes the limitation of traditional bag-of-words linguistic analysis. It incorporates machine learning over a massive number of sample articles to determine the sentiment direction of a word. Furthermore, the sentiment score of a word dynamically changes when more updated articles are added to the sample pool. For the sovereign credit risk, we use an extensive set of CDS data. Further decomposition is performed on the CDS spreads to get the risk premium and the default risk components with an affine credit valuation model. We perform a panel VAR regression on 22 sovereign CDS spreads from 2003 to 2014. We find that media tone explains and predicts sovereign CDS returns, as well as the default risk component. The effect on the CDS returns and the default component returns partially reverses within five weeks, whereas the effect on the risk premium reverses fully. The findings suggest that the overall impact on CDS returns is a mixture of noise and new information. This is consistent with the prevailing theories of investor over- and under-reaction. However, the noise signal appears to impact the risk premium and this leads to a temporary change in investors' appetite for credit exposure. The information signal influences the default risk component and leads to a reassessment of the fundamentals of sovereign economies.

Most of the 22 countries studied in Chapter 2 are emerging markets. One potential future research effort is to extend the sample with more developed countries. By comparing the impacts of media content on the developing versus developed countries, we can investigate the question whether the sovereign credit risks of advanced economies (as well as the corresponding default and risk premium components) respond to the media content in a similar fashion as the developing countries. In addition, Garcia (2013) finds the impact of news on stock returns concentrates in recessions. It would be interesting to see whether such a pattern can be observed in the sovereign CDS market. It is necessary to review the country-level economic history to define a precise crisis time period for each country.

Chapter 4 is an extension of our work in Chapter 3. We study the impact of media content on the corporate credit risk. Furthermore, we also investigate how a firm's equity return and credit return react to the same news. The company list contains 31 most liquid U.S. financial firms. For each firm, we collect the relevant news articles published by the Wall Street Journal (WSJ), and perform linguistic textual analysis. A firm-specific quantitative sentiment score measure is constructed. We then perform panel VAR regression of the equity and credit returns on the news. The results show that there is a significant delay in a firm's CDS return response to the WSJ news, in comparison to its equity return. Furthermore, both the equity and credit returns illustrate stronger and faster responses to news during the financial crisis period. The empirical findings support explanations that are related to the investor inattention. An informed trader opts for the equity market due to the high transaction cost in the CDS market. Traders in the CDS market, on the other hand, trade for non-fundamentals related reasons and hence pay less attention on news development as the equity traders. Furthermore, higher liquidity risk in the credit market during the financial crisis forces CDS traders to pay more attention on news in order to monitor market liquidity condition and avoid losses.

To support our arguments, two primary empirical efforts will be delivered in the future. Firstly, it is necessary to build a direct link between the information flow (price discovery) literature and the news sentiment literature. For example, if the VAR or the VECM model suggests that the price discovery occurs first in the equity market, it should have a simultaneous meaning that the equity market responds faster to news sentiment than the CDS market. To do so, it is necessary to extend the firm sample and include non-financial firms. In addition, a larger and comprehensive news articles sample will be constructed by including news reports from various resources, such as the Financial Times, the Reuters and the Bloomberg terminals. A parallel test comparison between the VAR (VECM) model between the two markets (for information discovery) versus the panel VAR model on news sentiment, with the updated data set, will help to establish the link between the two stands of literature. Secondly, in order to confirm the delayed reaction of the CDS return is the investor inattention story, exogenous shocks to the market liquidity condition will be identified to establish a causal relationship. Alternatively, we will perform advanced linguistic analysis to build a liquidity related news sentiment score and test its impact on firms' credit returns. The hypothesis would be if a CDS trader is a liquidity trader, and if investor attention is a scare resource, we would observe more rapid and more significant response of the credit return under the liquidity shocks (to the liquidity news, in comparison to non-liquidity related news).

Chapter 5 moves onto the real estate market of China, where it documents the impact of credit supply on real estate prices. The U.S. financial crisis of 2008 is used as an exogenous drop in the household credit provision in China. The variation in the treatment to this drop across the 31 provinces is used as a natural experiment to study the effect of changes in household credit on local real estate market and land market. The cross sectional variation is captured by using the financial deregulation process of China in opening up its local currency (RMB) business to foreign banks, between 1996 and 2006. The liberalisation of RMB to foreign banks expands the credit supply to local residents and corporates. The level of financial openness is defined as the number of foreign banking institutions established in the province by the end of 2006, when the geographical restriction on RMB business of foreign banks was completely removed. A higher number of foreign banks indicate a larger provision of foreign capital, as well as a better overseas investment facility. The influences of land price, public deficits, geographical constraints and other economic and fundamental factors on real estate prices are also considered. The results show that house price is more expensive in a more financially liberalised province. Furthermore, these provinces experience larger price depreciations in their real estate markets during the global financial crisis. In addition, the impact of credit supply on the land price is also studied in this chapter. The results show that the credit expansion which was induced by the financial liberalisation also increases the land price. However, there is no price depreciation illustrated by the land market during the financial crisis. One potential explanation is the 4 trillion RMB stimulus package issued by the Chinese central government in 2008, and the wide usage of the Local Government Financing Vehicles (LGFVs), which have both provided a massive amount of cheap credit in the land market. Thirdly, a more geographically constrained province has a higher house price. Such geographical constraints intensify the additional house price drops of a financial liberalised province during the global crisis.

Future work will focus on perfecting the house price measure, if possible. Also, it is important to collect the direct information on the credit supply which is provided by foreign banks in each province (if possible). More theoretical engagement will be placed on the relationship between house and land supply elasticities and prices, in order to study the extent to which land prices influence house prices. An empirical strategy will also be developed to study the relationship between the public deficit and house and land prices.

Bibliography

Abrigo, M., and I. Love, 2015, "Estimation of Panel Vector Autoregression in Stata: a Package of Programs," working paper, University of Hawaii at Manoa.

Acharya, V., I. Drechsler, and P. Schnabl, 2014, "A pyrrhic victory? Bank bailouts and sovereign credit risk," *Journal of Finance*, 69(6), 2689–2739.

Acharya, V., and T. C. Johnson, 2007, "Insider trading in credit derivatives," *Journal of Financial Economics*, 84(1), 110–141.

——— , 2010, "More insiders, more insider trading: Evidence from private-equity buyouts," *Journal of Financial Economics*, 98(3), 500–523.

Acharya, V., L. H. Pedersen, T. Philippon, and M. Richardson, 2017, "Measuring systemic risk," *Review of Financial Studies*, 30(1), 2–47.

Adelino, M., A. Schoar, and F. Severino, 2012, "Credit supply and house prices: evidence from mortgage market segmentation," working paper, National Bureau of Economic Research.

Adrian, T., and M. K. Brunnermeier, 2016, "CoVaR," *American Economic Review*, 106(7), 1705–41.

Alter, A., and Y. S. Schüler, 2012, "Credit spread interdependencies of European states and banks during the financial crisis," *Journal of Banking & Finance*, 36(12), 3444–3468.

Ang, A., and F. A. Longstaff, 2013, "Systemic sovereign credit risk: Lessons from the US and Europe," *Journal of Monetary Economics*, 60(5), 493–510.

Apergis, N., M. C. K. Lau, and L. Yarovaya, 2016, "Media sentiment and CDS spread spillovers: Evidence from the GIIPS countries," *International Review of Financial Analysis*, 47, 50–59.

Arora, N., P. Gandhi, and F. A. Longstaff, 2012, "Counterparty credit risk and the credit default swap market," *Journal of Financial Economics*, 103(2), 280–293.

Augustin, P., M. G. Subrahmanyam, D. Y. Tang, and S. Q. Wang, 2014, "Credit Default Swaps–A survey," *Foundations and Trends in Finance*, 9(1-2), 1–196.

Augustin, P., and R. Tédongap, 2016, "Real economic shocks and sovereign credit risk," *Journal of Financial and Quantitative Analysis*, 51(02), 541–587.

Badaoui, S., L. Cathcart, and L. El-Jahel, 2013, "Do sovereign credit default swaps represent a clean measure of sovereign default risk? A factor model approach," *Journal of Banking & Finance*, 37(7), 2392–2407.

Bai, J., and P. Collin-Dufresne, 2013, "The cds-bond basis," working paper, Georgetown University.

Barber, B. M., and T. Odean, 2008, "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors," *Review of Financial Studies*, 21(2), 785–818.

BBA, 2002, "2001/2002 Credit Derivatives Survey," *British Bankers Association. London.*

Beinstein, E., A. Sbityakov, K. Le, J. Goulden, D. Muench, S. Doctor, A. Granger, Y. Saltuk, and P. S. Allen, 2006, *Credit derivatives handbook.* J.P. Morgan, New York.

Berg, A., and J. Sachs, 1988, "The debt crisis structural explanations of country performance," *Journal of Development Economics*, 29(3), 271–306.

Berger, M. C., G. C. Blomquist, and K. S. Peter, 2008, "Compensating differentials in emerging labor and housing markets: Estimates of quality of life in Russian cities," *Journal of Urban Economics*, 63(1), 25–55.

Bhansali, V., R. Gingrich, and F. A. Longstaff, 2008, "Systemic credit risk: What is the market telling us?," *Financial Analysts Journal*, 64(4), 16–24.

Billio, M., M. Getmansky, D. Gray, A. W. Lo, R. C. Merton, and L. Pelizzon, 2014, "Sovereign, bank and insurance credit spreads: Connectedness and system networks," working paper, Ca'Foscari University of Venice.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon, 2012, "Econometric measures of connectedness and systemic risk in the finance and insurance sectors," *Journal of Financial Economics*, 104(3), 535 – 559.

Bisias, D., M. D. Flood, A. W. Lo, and S. Valavanis, 2012, "A survey of systemic risk analytics," *US Department of Treasury, Office of Financial Research*, (1).

Boehmer, E., and W. L. Megginson, 1990, "Determinants of Secondary Market Prices for Developing Country Syndicated Loans," *Journal of Finance*, 45(5), 1517–1540.

Bongaerts, D., F. De Jong, and J. Driessen, 2011, "Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market," *Journal of Finance*, 66(1), 203–240.

Brigo, D., and F. Mercurio, 2007, *Interest rate models-theory and practice: with smile, inflation and credit*. Springer Science & Business Media, New York.

Cahan, R. H., S. F. Cahan, T. Lee, and N. H. Nguyen, 2015, "Media content, accounting quality, and liquidity volatility," *European Accounting Review*, 0, 1–25.

Canova, F., and M. Ciccarelli, 2013, "Panel vector Autoregressive models: A survey," in *VAR Models in Macroeconomics-New Developments and Applications: Essays in Honor of Christopher A. Sims (Advances in Econometrics)*, ed. by F. Tomas, C. Hill, I. Jeliazkov, and J. Carlos. Emerald, Bingley, vol. 32, 205-246.

Case, K., and R. Shiller, 1987, "Prices of single-family homes since 1970: New indexes for four cities," *New England Economic Review*, 1, 45–56.

Cathcart, L., N. Gotthelf, M. Uhl, and Y. Shi, 2016, "Media content and sovereign credit risk," working paper, Imperial Business School.

CBRC, 1996, "The provisional regulations on foreign banking institutions Renminbi business on a trial basis in Shanghai Pudong area," *China Banking Regulatory Commission [in Chinese].*

——— , 2007, "Report on the opening-up of the Chinese banking sector," *China Banking Regulatory Commission.*

——— , 2008, “The 2007 annual report of China banking regulatory commission.,” *China Banking Regulatory Commission*.

Chen, L., D. A. Lesmond, and J. Wei, 2007, “Corporate yield spreads and bond liquidity,” *Journal of Finance*, 62(1), 119–149.

Claessens, S., and N. Horen, 2014, “Foreign banks: trends and impact,” *Journal of Money, Credit and Banking*, 46(1), 295–326.

Cohen, L., and A. Frazzini, 2008, “Economic links and predictable returns,” *Journal of Finance*, 63(4), 1977–2011.

Couderc, F., 2007, “Measuring risk on credit indices: On the use of the basis,” *Riskmetrics Journal*, 7(1), 61–87.

Coudert, V., and M. Gex, 2013, “Why the Greek CDS settlement did not lead to the feared meltdown,” *Financial stability Review*, 17, 135–150.

Cremers, M., J. Driessen, P. Maenhout, and D. Weinbaum, 2008, “Individual stock-option prices and credit spreads,” *Journal of Banking & Finance*, 32(12), 2706–2715.

Cruces, J. J., and C. Trebesch, 2013, “Sovereign defaults: The price of haircuts,” *American Economic Journal: Macroeconomics*, 5(3), 85–117.

Dale, F., R. Merton, and Z. Bodie, 2009, “New framework for measuring and managing macrofinancial risk and financial stability,” working paper, Central Bank of Chile.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, “Investor psychology and security market under-and overreactions,” *Journal of Finance*, 53(6), 1839–1885.

De Haas, R., and N. Van Horen, 2013, “Running for the exit? International bank lending during a financial crisis,” *Review of Financial Studies*, 26(1), 244–285.

Deinlnger, K., and H. Binswanger, 1999, “The evolution of the World Bank’s land policy: principles, experience, and future challenges,” *The World Bank Research Observer*, 14(2), 247–276.

DellaVigna, S., and J. M. Pollet, 2007, “Demographics and industry returns,” *American Economic Review*, 97(5), 1667–1702.

——— , 2009, “Investor inattention and Friday earnings announcements,” *Journal of Finance*, 64(2), 709–749.

Di Maggio, M., and A. Kermani, 2015, “Credit-induced boom and bust,” working paper, Harvard Business School.

Dieckmann, S., and T. Plank, 2012, “Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis,” *Review of Finance*, 16(4), 903–934.

Doms, M. E., and N. J. Morin, 2004, “Consumer sentiment, the economy, and the news media,” working paper, FRB of San Francisco.

Dooley, M., and M. Hutchison, 2009, “Transmission of the US subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis,” *Journal of International Money and Finance*, 28(8), 1331–1349.

Dougal, C., J. Engelberg, D. Garcia, and P. Christopher, 2012, "Journalsits and the stock market," *Review of Financial Studies*, 25, 639–679.

Driessen, J., P. J. Maenhout, and G. Vilkov, 2009, "The price of correlation risk: Evidence from equity options," *Journal of Finance*, 64(3), 1377–1406.

Duffie, D., A. Eckner, G. Horel, and L. Saita, 2009, "Frailty correlated default," *Journal of Finance*, 64(5), 2089–2123.

Duffie, D., J. Pan, and K. Singleton, 2000, "Transform analysis and asset pricing for affine jump-diffusions," *Econometrica*, 68(6), 1343–1376.

Duffie, D., L. H. Pedersen, and K. J. Singleton, 2003, "Modeling sovereign yield spreads: A case study of Russian debt," *Journal of Finance*, 58(1), 119–159.

Duffie, D., and K. Singleton, 1999, "Modeling term structures of defaultable bonds," *Review of Financial Studies*, 12(4), 687–720.

Duffie, D., and K. J. Singleton, 2003, *Credit risk: pricing, measurement, and management.* Princeton University Press, New Jersey.

Dzielinski, M., 2011, "News sensitivity and the cross-section of stock returns," working paper, Stockholm University.

Easley, D., M. O'hara, and P. S. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade," *Journal of Finance*, 53(2), 431–465.

Edwards, S., 1984, "LDC foreign borrowing and default risk: An empirical investigation, 1976-80," *American Economic Review*, 74(4), 726–734.

——— , 1986, "The pricing of bonds and bank loans in international markets: An empirical analysis of developing countries' foreign borrowing," *European Economic Review*, 30(3), 565–589.

Ehrmann, M., and D. Jansen, 2012, "The pitch rather than the pit: investor inattention during FIFA World Cup matches," working paper, European Central Bank.

Engelberg, J. E., and C. A. Parsons, 2011, "The causal impact of media in financial markets," *Journal of Finance*, 66(1), 67–97.

Farhi, E., S. P. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan, 2015, "Crash risk in currency markets," working paper, National Bureau of Economic Research.

Farnsworth, H., and T. Li, 2007, "The dynamics of credit spreads and ratings migrations," *Journal of Financial and Quantitative Analysis*, 42, 595–620.

Favara, G., and J. Imbs, 2015, "Credit supply and the price of housing," *American Economic Review*, 105(3), 958–992.

Fontana, A., and M. Scheicher, 2016, "An analysis of euro area sovereign CDS and their relation with government bonds," *Journal of Banking & Finance*, 62, 126–140.

Forte, S., and J. I. Peña, 2009, "Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS," *Journal of Banking & Finance*, 33(11), 2013–2025.

Frazzini, A., and O. A. Lamont, 2007, "The earnings announcement premium and trading volume," working paper, National Bureau of Economic Research.

Gao, H., H. Ru, and D. Y. Tang, 2016, "Subnational debt of China: The politics-finance nexus," working paper, University of Hong Kong.

Garcia, D., 2013, "Sentiment during recessions," *Journal of Finance*, 68(3), 1267–1300.

Georgoutsos, D. A., and P. M. Migiakis, 2013, "Heterogeneity of the determinants of euro-area sovereign bond spreads; what does it tell us about financial stability?," *Journal of Banking & Finance*, 37(11), 4650–4664.

Getmansky, M., A. W. Lo, and I. Makarov, 2004, "An econometric model of serial correlation and illiquidity in hedge fund returns," *Journal of Financial Economics*, 74(3), 529–609.

Geyer, A., S. Kossmeier, and S. Pichler, 2004, "Measuring systematic risk in EMU government yield spreads," *Review of Finance*, 8(2), 171–197.

Ghent, A. C., and M. T. Owyang, 2010, "Is housing the business cycle? Evidence from US cities," *Journal of Urban Economics*, 67(3), 336–351.

Glaeser, E. L., J. D. Gottlieb, and J. Gyourko, 2013, "Can cheap credit explain the housing boom?," in *Housing and the Financial Crisis*, ed. by E. L. Glaeser, and S. Todd. University of Chicago Press, Chicago, 301-359.

Glaeser, E. L., and B. A. Ward, 2009, "The causes and consequences of land use regulation: Evidence from Greater Boston," *Journal of Urban Economics*, 65(3), 265–278.

Greatrex, C. A., 2009, "The credit default swap market's reaction to earnings announcements," *Journal of Applied Finance*, 19(1-2).

Gyourko, J., A. Saiz, and A. Summers, 2008, "A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index," *Urban Studies*, 45(3), 693–729.

He, C., and G. Yeung, 2011, "The locational distribution of foreign banks in China: A disaggregated analysis," *Regional Studies*, 45(6), 733–754.

Heston, S. L., and N. R. Sinha, 2014, "News versus sentiment: Comparing textual processing approaches for predicting stock returns," working paper, University of Maryland.

Hillert, A., H. Jacobs, and S. Müller, 2014, "Media makes momentum," *Review of Financial Studies*, 27(12), 3467–3501.

Hilscher, J., J. M. Pollet, and M. Wilson, 2015, "Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets," *Journal of Financial and Quantitative Analysis*, 50(3), 543–567.

Hirshleifer, D., 2001, "Investor psychology and asset pricing," *Journal of Finance*, 61, 1533–1597.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang, 2004, "Do investors overvalue firms with bloated balance sheets?," *Journal of Accounting and Economics*, 38, 297–331.

Holtz-Eakin, D., W. Newey, and H. S. Rosen, 1988, "Estimating vector autoregressions with panel data," *Econometrica*, 56(6), 1371–1395.

Hongyuan, C., and X. Wang, 2007, "Analysis on development of foreign banks in China," *China Finance*, (14), 44–46 [in Chinese].

Huang, D. J., C. K. Leung, and B. Qu, 2015, "Do bank loans and local amenities explain Chinese urban house prices?," *China Economic Review*, 34, 19–38.

Huang, X., H. Zhou, and H. Zhu, 2009, "A framework for assessing the systemic risk of major financial institutions," *Journal of Banking & Finance*, 33(11), 2036–2049.

ISDA, 2007, "ISDA 2007 Year-End Market Survey," *International Swaps and Derivatives Association.*

Jeanneret, A., 2015, "The Dynamics of sovereign credit risk," *Journal of Financial and Quantitative Analysis*, 50(05), 963–985.

Jegadeesh, N., and D. Wu, 2013, "Word power: A new approach for content analysis," *Journal of Financial Economics*, 110(3), 712–729.

Jobst, A. A., and D. F. Gray, 2013, "Systemic contingent claims analysis: Estimating market-implied systemic risk," working paper, International Monetary Fund.

Junge, B., and A. B. Trolle, 2015, "Liquidity risk in credit default swap markets," *Swiss Finance Institute Research Paper*, 1, 13–65.

Kallestrup, R., D. Lando, and A. Murgoci, 2016, "Financial sector linkages and the dynamics of bank and sovereign credit spreads," *Journal of Empirical Finance*, 38, 374–393.

Kelly, B., H. Lustig, and S. Van Nieuwerburgh, 2016, "Too-systemic-to-fail: What option markets imply about sector-wide government guarantees," *American Economic Review*, 106(6), 1278–1319.

Kelly, B., L. Pástor, and P. Veronesi, 2016, "The price of political uncertainty: Theory and evidence from the option market," *Journal of Finance*, 71(5), 2417–2480.

Kiyotaki, N., A. Michaelides, and K. Nikolov, 2011, "Winners and losers in housing markets," *Journal of Money, Credit and Banking*, 43(2-3), 255–296.

Leamer, E. E., 2007, "Housing is the business cycle," working paper, National Bureau of Economic Research.

——— , 2015, "Housing really is the business cycle: What survives the lessons of 2008-09?," *Journal of Money, Credit and Banking*, 47(S1), 43–50.

Lehar, A., 2005, "Measuring systemic risk: A risk management approach," *Journal of Banking & Finance*, 29(10), 2577–2603.

Li, H., T. Li, and X. Yang, 2014, "Sovereign CDS spreads with credit rating," working paper, Cheung Kong Graduate School of Business.

Liebmann, M., A. G. Orlov, and D. Neumann, 2016, "The tone of financial news and the perceptions of stock and CDS traders," *International Review of Financial Analysis*, 46, 159–175.

Lin, H., 2011, "Foreign bank entry and firms access to bank credit: evidence from China," *Journal of Banking & Finance*, 35(4), 1000–1010.

Longstaff, F. A., S. Mithal, and E. Neis, 2005, "Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market," *Journal of Finance*, 60(5), 2213–2253.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton, 2011, "How sovereign is sovereign credit risk?," *American Economic Journal: Macroeconomics*, 3(2), 75–103.

Loughran, T., and B. McDonald, 2011, "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *Journal of Finance*, 66(1), 35–65.

Mamaysky, H., and P. Glasserman, 2016, "Does unusual news forecast market stress?," working paper, Columbia University.

Marsh, I. W., and W. Wagner, 2012, "Why is price discovery in credit default swap markets news-specific?," working paper, Cass Business School.

Mauro, P., N. Sussman, and Y. Yafeh, 2002, "Emerging market spreads: Then versus now," *Quarterly Journal of Economics*, 117(2), 695–733.

Merton, R. C., 1974, "On the pricing of corporate debt: The risk structure of interest rates," *Journal of Finance*, 29(2), 449–470.

Mian, A., and A. Sufi, 2009, "The Consequences of mortgage credit expansion: Evidence from the US mortgage default crisis," *Quarterly Journal of Economics*, 124(4), 1449–1496.

——— , 2010, "The Great Recession: Lessons from microeconomic data," *American Economic Review*, 100(2), 51–56.

——— , 2014, *House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again*. University of Chicago Press, Chicago.

Monfort, A., and J.-P. Renne, 2014, "Decomposing euro-area sovereign spreads: credit and liquidity risks," *Review of Finance*, 18(6), 2103–2151.

Ni, S. X., and J. Pan, 2011, "Trading puts and CDS on stocks with short sale ban," working paper, Hong Kong University of Science and Technology.

Norden, L., 2009, "Credit derivatives, corporate news, and credit ratings," working paper, University of Mannheim.

Norden, L., and M. Weber, 2004, "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements," *Journal of Banking & Finance*, 28(11), 2813–2843.

——— , 2009, "The co-movement of credit default swap, bond and stock markets: An empirical analysis," *European Financial Management*, 15(3), 529–562.

Oates, W. E., 1969, "The effects of property taxes and local public spending on property values: An empirical study of tax capitalization and the Tiebout hypothesis," *Journal of Political Economy*, 77(6), 957–971.

O'Kane, D., 2011a, "Force-fitting CDS spreads to CDS index swaps," *Journal of Derivatives*, 18(3), 61–74.

——— , 2011b, *Modelling single-name and multi-name credit derivatives*, vol. 573. John Wiley & Sons, West Sussex.

Pan, J., and K. J. Singleton, 2008, "Default and recovery implicit in the term structure of sovereign CDS spreads," *Journal of Finance*, 63(5), 2345–2384.

Pástor, L., and P. Veronesi, 2012, "Uncertainty about government policy and stock prices," *Journal of Finance*, 67(4), 1219–1264.

——— , 2013, "Political uncertainty and risk premia," *Journal of Financial Economics*, 110(3), 520–545.

Qian, Y., and G. Roland, 1998, "Federalism and the soft budget constraint," *American Economic Review*, 88(5).

Reinhart, C. M., and K. S. Rogoff, 2009, *This Time is Different: Eight Centuries of Financial Folly*. Princeton University Press, New Jersey.

Remolona, E. M., M. Scatigna, and E. Wu, 2007, "Interpreting sovereign spreads," *BIS Quarterly Review*.

——— , 2008, "The dynamic pricing of sovereign risk in emerging markets: Fundamentals and risk aversion," *Journal of Fixed Income*, 17(4), 57–71.

Rodríguez-Moreno, M., and J. I. Peña, 2013, "Systemic risk measures: The simpler the better?," *Journal of Banking & Finance*, 37(6), 1817–1831.

Roloack, J., 1982, "Wages, rents, and the quality of life," *Journal of Political Economy*, 90(6), 1257–1258.

Saiz, A., 2010, "The geographic determinants of housing supply," *Quarterly Journal of Economics*, 125(3), 1253–1296.

Schweikhard, F. A., and Z. Tsesmelidakis, 2012, "The impact of government interventions on CDS and equity markets," working paper, Saïd Business School and Oxford-Man Institute, University of Oxford.

Segoviano Basurto, M., and C. Goodhart, 2009, "Banking stability measures," working paper, International Monetary Fund.

Sinha, N. R., 2016, "Underreaction to news in the US stock market," *Quarterly Journal of Finance*, 6(2), 105–165.

Smales, L. A., 2014, "News sentiment in the gold futures market," *Journal of Banking & Finance*, 49, 275–286.

Stock, J. H., and M. W. Watson, 1993, "A simple estimator of cointegrating vectors in higher order integrated systems," *Econometrica*, 61(4), 783–820.

Takats, E., 2010, "Was it credit supply? Cross-border bank lending to emerging market economies during the financial crisis," *BIS Quarterly Review*.

Tang, D. Y., and H. Yan, 2010, "Market conditions, default risk and credit spreads," *Journal of Banking & Finance*, 34(4), 743 – 753.

——— , 2013, "What moves CDS spreads?," working paper, University of Hong Kong.

Tarashev, N., and H. Zhu, 2008, "The pricing of correlated default risk: evidence from the credit derivatives market," *Journal of Fixed Income*, 18(1), 5–24.

Tetlock, P., M. Saar-Tsechansky, and S. Macskassy, 2008, "Investor psychology and asset pricing," *Journal of Finance*, 63, 1437–1467.

Tetlock, P. C., 2007, "Giving content to investor sentiment: The role of media in the stock market," *Journal of Finance*, 62(3), 1139–1168.

Tett, G., 2009, *Fool's gold: How the bold dream of a small tribe at J.P. Morgan was corrupted by Wall Street greed and unleashed a catastrophe*. Simon and Schuster, Hachette.

Tomz, M., and M. Wright, 2013, "Empirical research on sovereign debt and default," *Annual Review of Economics*, 5(1), 247–272.

Tripathy, J., 2015, "Effect of household credit on sectoral composition: Evidence from Mexico," working paper, Universitat Pompeu Fabra.

Uhl, M. W., M. Pedersen, and O. Malitius, 2015, "What's in the News? Using News sentiment momentum for tactical asset allocation," *The Journal of Portfolio Management*, 41(2), 100–112.

Wei, X., H. Fang, Q. Gu, and L. Zhou, 2015, "Demystifying the Chinese housing boom," in *NBER Macroeconomics Annual*, ed. by E. Martin, and P. Jonathan. University of Chicago Press, Chicago, vol. 30, 105-166.

Wu, G. L., Q. Feng, and P. Li, 2015, "Does local governments' budget deficit push up housing prices in China?," *China Economic Review*, 35, 183–196.

Wu, J., Y. Deng, and H. Liu, 2014, "House price index construction in the nascent housing market: The case of China," *Journal of Real Estate Finance and Economics*, 48(3), 522–545.

Wu, J., J. Gyourko, and Y. Deng, 2012, "Evaluating conditions in major Chinese housing markets," *Regional Science and Urban Economics*, 42(3), 531–543.

——— , 2016, "Evaluating the risk of Chinese housing markets: what we know and what we need to know," *China Economic Review*, 39, 91–114.

Zhang, B. Y., H. Zhou, and H. Zhu, 2009, "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms," *Review of Financial Studies*, 22(12), 5099–5131.

Zhang, F. X., 2008, "Market expectations and default risk premium in credit default swap prices: A study of Argentine default," *Journal of Fixed Income*, 18(1), 37–55.

Zhang, H., and C. Yang, 2007, "Locational choice of foreign banks in China and their investment motives," *Financial Research*, 9, 160–172 [in Chinese].

Zheng, S., J. Cao, and M. E. Kahn, 2011, "China's rising demand for" green cities": Evidence from cross-city real estate price hedonics," working paper, National Bureau of Economic Research.

Zheng, S., Y. Fu, and H. Liu, 2009, "Demand for urban quality of living in China: evolution in compensating land-rent and wage-rate differentials," *Journal of Real Estate Finance and Economics*, 38(3), 194–213.

Zhu, H., 2006, "An empirical comparison of credit spreads between the bond market and the credit default swap market," *Journal of Financial Services Research*, 29(3), 211–235.

Appendix A

A.1 Basket-Index Spread: Default Intensity Model

A.1.1 Difference between a Basket of Single-Name CDS and CDS Index

This appendix provides a theoretical illustration on the difference in insurance price between a basket of single-name CDS and a CDS index. The following is built on the default intensity model, therefore, based on the market-implied measure (risk-neutral measure).

Assume there are two banks, bank A and bank B. The default probability of each bank is governed by a default intensity λ^A and λ^B, whose processes are defined as below:

$$
\begin{aligned}
\lambda_A &= a_1 + b_1\lambda_s + \sigma_1\epsilon_1 \\
\lambda_B &= a_2 + b_2\lambda_s + \sigma_2\epsilon_2 \\
\lambda_s &= \mu_s + \sigma_s\epsilon \qquad \epsilon_1, \quad \epsilon_2, \quad \epsilon \sim N(0,1)
\end{aligned}
$$

wherein λ_s is the default intensity of a systemic risk factor, whose dynamics may lead to a default of bank A or bank B. Furthermore, $\epsilon_1, \quad \epsilon_2$ are the idiosyncratic risks specific to bank A and bank B respectively. ϵ is the random error term in the default intensity of systemic risk factor. The default of bank A (B) can be caused by individual firm-specific idiosyncratic shocks, as well as systemic-wide shocks. Therefore, the survival rates of bank A or bank B at time t are

$$
\begin{aligned}
\mathbb{P}(\tau_A > t) &= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1\lambda_s + \sigma_1\epsilon_1)ds}] \\
&= \exp^{-(a_1 + b_1\mu_s + \frac{1}{2}\sigma_1^2 + \frac{1}{2}b_1^2\sigma_s^2)t}
\end{aligned}
$$

Consider a basket of single-name CDSs on bank A and bank B. The survival probability of the basket is the probability there is no default on either bank A or bank B, which could be expressed as below:

$$
\begin{aligned}
\mathbb{P}(\tau_A > t) \cap \mathbb{P}(\tau_B > t) &= \mathbb{E}[\exp^{-\int_0^t (\lambda_A + \lambda_B)ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1\lambda_s + \sigma_1\epsilon_1 + a_2 + b_2\lambda_s + \sigma_2\epsilon_2)ds}] \\
&= \exp^{-[(a_1+a_2) + (b_1+b_2)\mu_s + \frac{1}{2}(\sigma_1^2 + \sigma_2^2 + (b_1^2 + b_2^2 + 2b_1b_2)\sigma_s^2)]t}
\end{aligned}
$$

Assume the market is efficient, constructing the portfolio diversifies the idiosyncratic risks in individual banks. Therefore, a CDS index with constituents bank A and B only exposes to the systemic risk. The survival probability of such index is expressed as:

$$\begin{aligned}\mathbb{P}(\tau_s > t) &= \mathbb{E}[\exp^{-\int_0^t \lambda_s ds}] \\ &= \mathbb{E}[\exp^{-\int_0^t (\mu_s + \sigma_s \epsilon) ds}] \\ &= \exp^{-(\mu_s + \frac{1}{2}\sigma_s^2)t}\end{aligned}$$

For simplicity, set $a_1 = a_2 = 0$ and $\sigma_1 = \sigma_2 = 0$, the ratio of survival rates between the basket insuring the default of both banks versus the index is

$$\frac{\mathbb{P}(\tau_A > t) \cap \mathbb{P}(\tau_B > t)}{\mathbb{P}(\tau_s > t)} = \exp^{-[(b_1+b_2-1)\mu_s + \frac{1}{2}(b_1^2+b_2^2+2b_1b_2-1)\sigma_s^2]t}$$

A.1.2 With Government Bailout on the Systemic Default Risk

Now consider the government takes interventions during the financial crisis to avoid the system collapse. And the government bailout action helps to reduce the default intensity of the systemic risk λ_s.

$$\begin{aligned}\lambda_A &= a_1 + b_1\lambda_s + \sigma_1\epsilon_1 \\ \lambda_B &= a_2 + b_2\lambda_s + \sigma_2\epsilon_2 \\ \lambda_s &= (\mu_s - \Delta\mu_s \mathbf{1}_{BL}) + \sigma_s\epsilon \qquad \epsilon_1, \quad \epsilon_2, \quad \epsilon \sim N(0,1)\end{aligned}$$

wherein $\mathbf{1}_{BL}$ is an indicator function with value of 1 if there is a bailout action taken by the government, and 0 otherwise.

$$\begin{aligned}\mathbb{P}(\tau_A > t) &= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1(\mu_s - \Delta\mu_s\mathbf{1}_{BL} + \sigma_s\epsilon) + \sigma_1\epsilon_1) ds}] \\ &= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1\mu_s + b_1\sigma_s\epsilon + \sigma_1\epsilon_1 - b_1\Delta\mu_s\mathbf{1}_{BL}) ds}] \\ &= \exp^{-(a_1 + b_1\mu_s + \frac{1}{2}\sigma_1^2 + \frac{1}{2}b_1^2\sigma_s^2)t}\, \mathbb{E}[\exp^{\int_0^t b_1\Delta\mu_s\mathbf{1}_{BL} ds}]\end{aligned}$$

The government bailout action also increases the survival rate of the individual bank A (B) by reducing the trend term in the systemic default probability.

$$\begin{aligned}
\mathbb{P}(\tau_A > t) \cap \mathbb{P}(\tau_B > t) &= \mathbb{E}[\exp^{-\int_0^t (\lambda_A + \lambda_B) ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_1 \epsilon_1 + a_2 + b_2(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_2 \epsilon_2) ds}] \\
&= \exp^{-[(a_1+a_2)+(b_1+b_2)\mu_s + \frac{1}{2}(\sigma_1^2 + \sigma_2^2 + (b_1^2 + b_2^2 + 2b_1 b_2)\sigma_s^2)]t} \, \mathbb{E}[\exp^{\int_0^t (b_1+b_2)\Delta\mu_s \mathbf{1}_{BL} ds}]
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(\tau_s > t) &= \mathbb{E}[\exp^{-\int_0^t \lambda_s ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) ds}] \\
&= \exp^{-(\mu_s + \frac{1}{2}\sigma_s^2)t} \, \mathbb{E}[\exp^{\int_0^t \Delta\mu_s \mathbf{1}_{BL} ds}]
\end{aligned}$$

$$\frac{\mathbb{P}(\tau_A > t) \cap \mathbb{P}(\tau_B > t)}{\mathbb{P}(\tau_s > t)} = \exp^{-[(b_1+b_2-1)\mu_s + \frac{1}{2}(b_1^2 + b_2^2 + 2b_1 b_2 - 1)\sigma_s^2]t} \, \mathbb{E}[\exp^{\int_0^t (b_1+b_2-1)\Delta\mu_s \mathbf{1}_{BL} ds}]$$

A.1.3 With Government Bailout on the Systemic Default Risk & Bank's Loading on Systemic Risk

The following is the scenario when the government bailout not only reduces the systemic risk, but also reduces individual bank's loading of the systemic risk. Similar reasoning would be applied from above.

$$\begin{aligned}
\lambda_A &= a_1 + (b_1 - \Delta b_1 \mathbf{1}_{BL})\lambda_s + \sigma_1 \epsilon_1 \\
\lambda_B &= a_2 + (b_2 - \Delta b_2 \mathbf{1}_{BL})\lambda_s + \sigma_2 \epsilon_2 \\
\lambda_s &= (\mu_s - \Delta\mu_s \mathbf{1}_{BL}) + \sigma_s \epsilon \qquad \epsilon_1, \quad \epsilon_2, \quad \epsilon \sim N(0,1)
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(\tau_A > t) &= \mathbb{E}[\exp^{-\int_0^t (a_1 + (b_1 - \Delta b_1 \mathbf{1}_{BL})(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_1 \epsilon_1) ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1\mu_s + b_1 \sigma_s \epsilon + \sigma_1 \epsilon_1 - \Delta b_1 \mu_s \mathbf{1}_{BL} - b_1 \Delta\mu_s \mathbf{1}_{BL} - \Delta b_1 \sigma_s \epsilon \mathbf{1}_{BL} + \Delta b_1 \Delta\mu_s \mathbf{1}_{BL} \mathbf{1}_{BL}) ds}] \\
&= \exp^{-(a_1 + b_1\mu_s + \frac{1}{2}\sigma_1^2 + \frac{1}{2}b_1^2\sigma_s^2)t} \, \mathbb{E}[\exp^{\int_0^t (\Delta b_1(\mu_s + \sigma_s \epsilon)\mathbf{1}_{BL} + \Delta\mu_s(b_1 - \Delta b_1 \mathbf{1}_{BL})\mathbf{1}_{BL} ds}]
\end{aligned}$$

$$
\begin{aligned}
\mathbb{P}(\tau_A > t) \cap \mathbb{P}(\tau_B > t) &= \mathbb{E}[\exp^{-\int_0^t (\lambda_A + \lambda_B) ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (a_1 + (b_1 - \Delta b_1 \mathbf{1}_{BL})(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_1 \epsilon_1 + a_2 + (b_2 - \Delta b_2 \mathbf{1}_{BL})(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_2 \epsilon_2) ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (a_1 + b_1(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_1 \epsilon_1 - \Delta b_1 \mathbf{1}_{BL}(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon)} \\
&\quad {}^{+ a_2 + b_2(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \sigma_2 \epsilon_2 - \Delta b_2 \mathbf{1}_{BL}(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon)) ds}] \\
&= \exp^{-[(a_1 + a_2) + (b_1 + b_2)\mu_s + \frac{1}{2}(\sigma_1^2 + \sigma_2^2 + (b_1^2 + b_2^2 + 2 b_1 b_2)\sigma_s^2)]t} \\
&\quad \mathbb{E}[\exp^{((\Delta b_1 + \Delta b_2)\mathbf{1}_{BL}(\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) + \Delta\mu_s \mathbf{1}_{BL}(b_1 + b_2) ds)}]
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{P}(\tau_s > t) &= \mathbb{E}[\exp^{-\int_0^t \lambda_s ds}] \\
&= \mathbb{E}[\exp^{-\int_0^t (\mu_s - \Delta\mu_s \mathbf{1}_{BL} + \sigma_s \epsilon) ds}] \\
&= \exp^{-(\mu_s + \frac{1}{2}\sigma_s^2)t}\, \mathbb{E}[\exp^{\int_0^t \Delta\mu_s \mathbf{1}_{BL} ds}]
\end{aligned}
$$

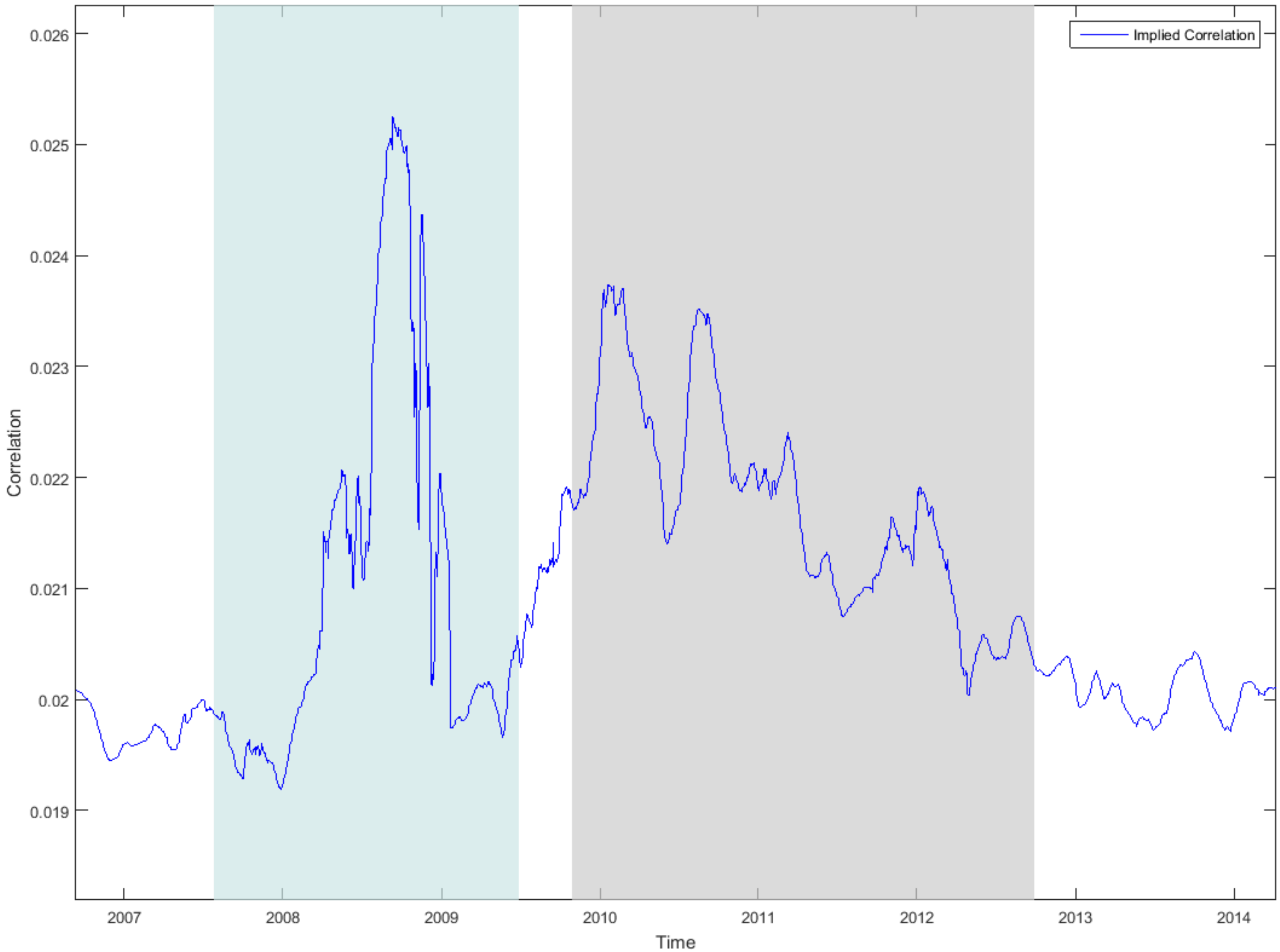
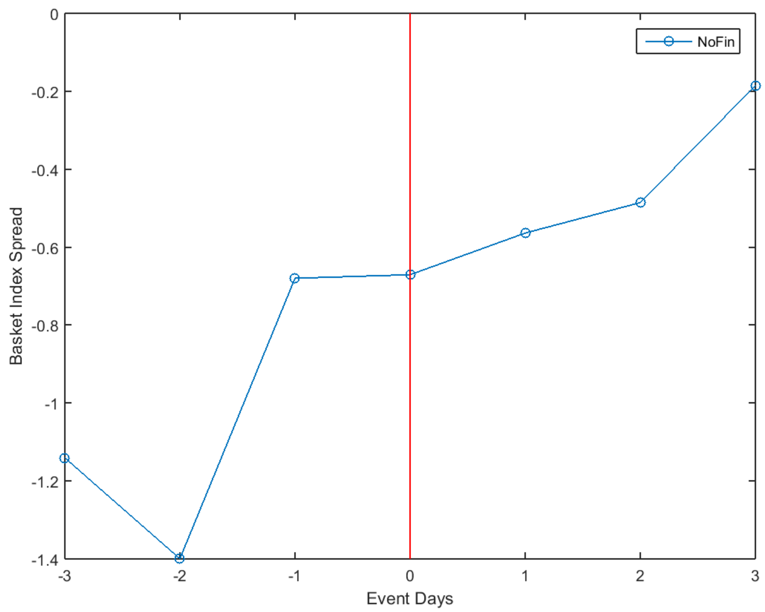


Figure A.1. Risk-Neutral Implied Default Correlation: Non Financial Sector

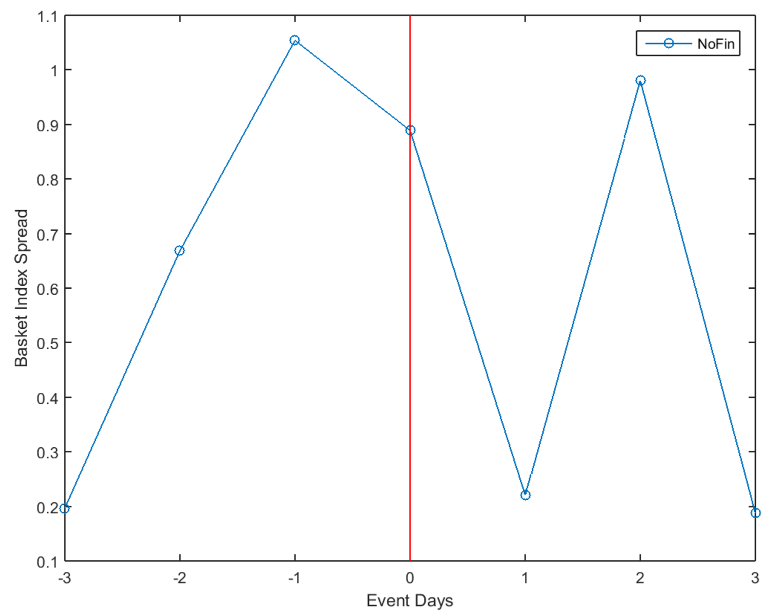
The figure plots the time series of the risk-neutral default correlation for the non-financial sector. The sample period is from September 2006 to April 2014. The cyan vertical bar represents the U.S. financial crisis. The grey vertical bar represents the European sovereign crisis.

Figure A.2. Risk-Neutral Implied Default Correlation: Sovereign Sector

The figure plots the time series of the risk-neutral default correlation for the non-financial sector. The sample period is from September 2009 to April 2014. The grey vertical bar represents the European sovereign crisis.



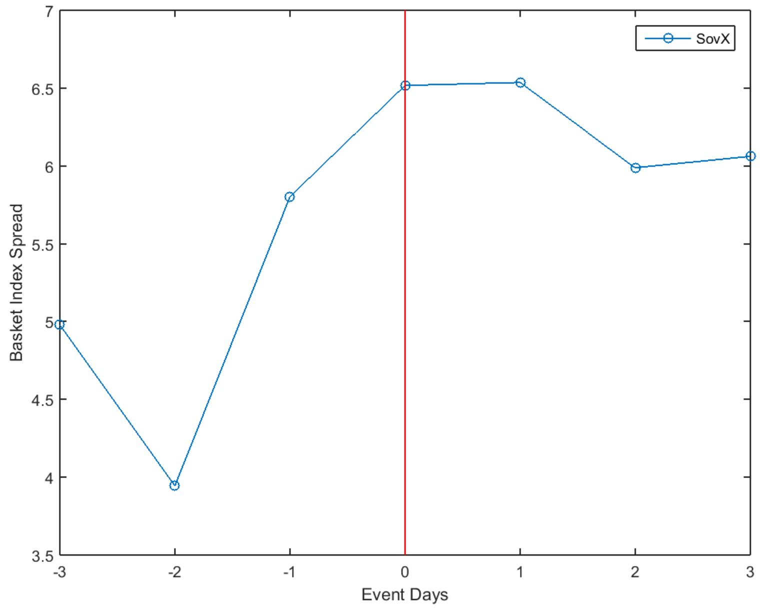
(a) Positive News



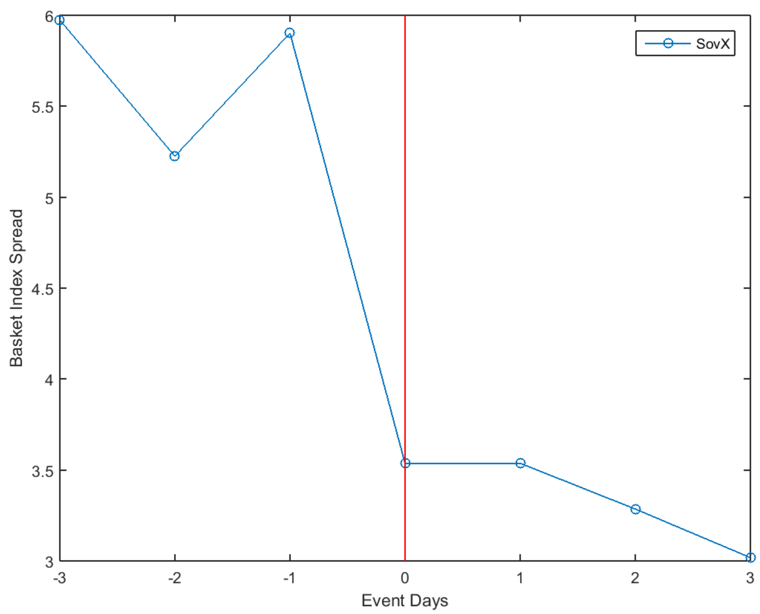
(b) Negative News

Figure A.3. Average Basket-Index Spread Across Event Days: Non Financial Sector

The figures plot the average financial basket-index spread outside a +/- 3-day interval around government news announcement of the European non-financial sector. The top panel uses positive news and the lower panel uses negative news.



(a) Positive News



(b) Negative News

Figure A.4. Average Basket-Index Spread Across Event Days: Sovereign Sector

The figures plot the average financial basket-index spread outside a +/- 3-day interval around government news announcement of the European sovereign sector. The top panel uses positive news and the lower panel uses negative news.

Appendix B

B.1 Additional Regression Results: Sovereign Credit Risk

Table B.1. Regression Results: CDS^Q Return

This table reports the coefficients of the robust regression of five-year CDS simple returns on explanatory variables. The global risk factors include US stock excess return, VIX volatility premium, term premium, changes in 5-year treasure rates, investment grade spread and high yield premium. Local risk variables contain the local exchange rate return, local equity risk return. Sovereign spreads are the global sovereign spreads and regional sovereign spreads. In addition, news sentiment is also included. The sample period spans from January 2003 to April 2014 at weekly frequency. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	BGARIA	**BRAZIL**	**CHILE**	**CHINA**	**COLOM**	**CROATI**	**ISRAEL**
Global risk factors							
US stock market	-0.008***	-0.010***	-0.005*	-0.003	-0.011***	-0.008***	-0.003
Volatility premium	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
Term premium	0.001	-0.000	0.000	0.003***	-0.000	0.000	0.002**
Treasury market	0.098***	0.219***	0.071**	0.155***	0.219***	0.077***	0.060***
Investment grade	-0.005***	-0.003***	-0.003**	-0.004*	-0.003***	-0.005***	-0.002
High yield	1.563***	1.214***	1.565***	1.447***	1.407***	1.501***	0.924***
Local variables							
Exchange return	-0.137	-0.371***	0.319	-0.353	-0.072	0.079	-0.239
Stock return	0.116	-0.195***	-0.168	0.015	-0.099	0.058	0.067
Sovereign spreads							
Regional spread	0.059	0.118	0.284**	0.278*	0.149*	0.089	0.348***
Global spread	0.898***	0.979***	0.445***	0.946***	1.024***	0.846***	0.362***
News sentiment	-0.112***	-0.089***	-0.123***	-0.109***	-0.093***	-0.114***	-0.075***
Constant	0.009**	0.002	0.005	0.004	-0.001	0.008**	0.000
N	448	568	568	568	568	568	568
Adjusted R^2	0.782	0.889	0.589	0.769	0.890	0.748	0.579

Table B.2. Regression Results: CDS^Q Return (Continue)

	JAPAN	**KOREA**	**MALAYS**	**MEX**	**PANAMA**	**PHILIP**	**POLAND**
Global risk factors							
US stock market	-0.001	0.004	-0.000	-0.009***	-0.008***	-0.002	-0.007**
Volatility premium	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
Term premium	-0.002	0.003*	0.003**	0.001**	0.002	0.001**	0.001*
Treasury market	0.103**	0.130***	0.121***	0.190***	0.183***	0.119***	0.087***
Investment grade	-0.004	-0.006***	-0.005***	-0.005***	-0.002***	-0.002*	-0.005***
High yield	1.068***	1.528***	1.371***	1.454***	1.499***	0.942***	1.598***
Local variables							
Exchange return	0.434	-0.348	-0.531	-0.857***		-1.237***	-0.319**
Stock return	-0.281	-0.012	-0.187	0.022	-0.185**	-0.302***	-0.098
Sovereign spreads							
Regional spread	0.425***	-0.074	-0.037	0.065	0.021	0.275***	0.080
Global spread	0.045	1.051***	1.096***	0.953***	1.015***	0.418***	0.926***
News sentiment	-0.128***	-0.116***	-0.058**	-0.098***	-0.083***	-0.053***	-0.097***
Constant	0.004	0.002	0.000	0.001	0.001	-0.002	0.007**
N	568	568	568	568	257	568	568
Adjusted R^2	0.366	0.700	0.782	0.842	0.922	0.754	0.707

	QATAR	**ROMANI**	**RUSSIA**	**SLOVAK**	**SOAF**	**UKRAIN**	**VENZ**
Global risk factors							
US stock market	-0.000	-0.006*	-0.007	-0.002	-0.006	-0.007**	-0.007**
Volatility premium	-0.002***	-0.002***	-0.002	-0.004***	-0.002***	-0.000	-0.001
Term premium	0.000	0.001	0.000	0.003	0.002**	0.001	-0.000
Treasury market	0.078***	0.055***	0.150***	0.043	0.152***	0.079**	0.127***
Investment grade	0.001	-0.005***	-0.003*	-0.003***	-0.005***	-0.000	-0.002
High yield	0.974***	1.427***	1.493***	1.418***	1.397***	1.313***	0.973***
Local variables							
Exchange return	0.677	-0.240	-0.343	-0.079	-0.350**	-0.051	0.047
Stock return	-0.167*	0.043	-0.369**	-0.138	0.157	-0.248***	-0.194**
Sovereign spreads							
Regional spread	0.398***	-0.116*	0.281	0.208	0.807***	0.275***	0.099
Global spread	0.221**	0.926***	0.493***	0.872***	0.074	0.321***	0.527***
News sentiment	-0.122***	-0.095***	-0.072*	-0.200***	-0.078**	-0.069*	-0.089***
Constant	0.005	0.007**	0.007	0.001	0.003	0.010*	0.006*
N	448	422	568	283	568	397	568
Adjusted R^2	0.567	0.786	0.659	0.755	0.671	0.575	0.511

Table B.3. Regression Results with Regional News: CDS^{Q} Return

This table reports the coefficients of robust regression of five-year CDS simple returns on explanatory variables. The news sentiment includes only the local regional news sentiment and the debt news sentiment. The global risk factors include US stock excess return, VIX volatility premium, term premium, changes in 5-year treasure rates, investment grade spread and high yield premium. Local risk variables contain the local exchange rate return, local equity risk return. Sovereign spreads are the global sovereign spreads and regional sovereign spreads. The sample period spans from January 2003 to April 2014 at weekly frequency. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	BGARIA	**BRAZIL**	**CHILE**	**CHINA**	**COLOM**	**CROATI**
Global risk factors						
US stock market	-0.008***	-0.010***	-0.005*	-0.003	-0.012***	-0.008***
Volatility premium	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***	-0.002***
Term premium	0.001	-0.000	0.000	0.003***	-0.000	0.000
Treasury market	0.099***	0.222***	0.075**	0.157***	0.221***	0.077***
Investment grade	-0.005***	-0.003***	-0.003**	-0.003*	-0.002***	-0.005***
High yield	1.571***	1.230***	1.589***	1.466***	1.420***	1.509***
Local variables						
Exchange return	-0.200	-0.373***	0.322	-0.158	-0.078	0.040
Stock return	0.100	-0.197***	-0.171	0.014	-0.114*	0.030
Sovereign spreads						
Regional spread	0.060	0.121	0.290**	0.271*	0.152*	0.085
Global spread	0.891***	0.971***	0.435***	0.947***	1.014***	0.842***
Region news sentiment	-0.090***	-0.048***	-0.066***	-0.086**	-0.043***	-0.087***
Constant	0.013***	-0.001	0.001	0.001	-0.004	0.013***
N	448	568	568	568	568	568
Adjusted R^2	0.778	0.886	0.583	0.763	0.886	0.743

Table B.4. Regression Results with Regional News: CDS^Q Return (Continue)

	JAPAN	**KOREA**	**MALAYS**	**MEX**	**PANAMA**	**PHILIP**
Global risk factors						
US stock market	-0.002	0.004	-0.001	-0.009***	-0.008***	-0.003
Volatility premium	-0.003***	-0.004***	-0.003***	-0.003***	-0.002***	-0.003***
Term premium	-0.002	0.003*	0.003**	0.001*	0.002	0.001**
Treasury market	0.105***	0.132***	0.122***	0.194***	0.182***	0.120***
Investment grade	-0.004	-0.006***	-0.004***	-0.005***	-0.002***	-0.002*
High yield	1.089***	1.533***	1.380***	1.472***	1.524***	0.952***
Local variables						
Exchange return	0.479	-0.445	-0.558	-0.863***		-1.221***
Stock return	-0.278	-0.028	-0.192	0.029	-0.216**	-0.289***
Sovereign spreads						
Regional spread	0.414***	-0.085	-0.040	0.071	0.017	0.268***
Global spread	0.047	1.045***	1.096***	0.946***	1.010***	0.422***
Region news sentiment	-0.098**	-0.049	-0.031	-0.070***	-0.023	-0.068***
Constant	0.000	-0.002	-0.002	-0.001	-0.000	-0.003
N	568	568	568	568	257	568
Adjusted R^2	0.357	0.691	0.780	0.842	0.919	0.755

	POLAND	**ROMANI**	**RUSSIA**	**SLOVAK**	**UKRAIN**	**VENZ**
Global risk factors						
US stock market	-0.007**	-0.006*	-0.007	-0.002	-0.007**	-0.007**
Volatility premium	-0.002***	-0.002***	-0.002	-0.004***	-0.000	-0.001
Term premium	0.001*	0.001	0.000	0.003	0.001	-0.000
Treasury market	0.087***	0.055**	0.150***	0.047	0.079**	0.129***
Investment grade	-0.005***	-0.005***	-0.003*	-0.003***	-0.000	-0.002
High yield	1.604***	1.439***	1.500***	1.432***	1.305***	0.988***
Local variables						
Exchange return	-0.345**	-0.286*	-0.346	0.021	-0.035	0.049
Stock return	-0.104	0.039	-0.364**	-0.148	-0.238***	-0.193**
Sovereign spreads						
Regional spread	0.078	-0.114*	0.282	0.213*	0.279***	0.104
Global spread	0.921***	0.919***	0.492***	0.859***	0.318***	0.519***
Region news sentiment	-0.081***	-0.078***	-0.087**	-0.174***	-0.112**	-0.061***
Constant	0.012***	0.012***	0.013	0.013**	0.018**	0.004
N	568	422	568	283	397	568
Adjusted R^2	0.705	0.784	0.662	0.755	0.581	0.510

Table B.5. Regression Results with Global News: CDS^Q Return

This table reports the coefficients of robust regression of five-year CDS simple returns on explanatory variables. The news sentiment includes all global news contents that exclude the local media coverage in the region of country. The global risk factors include US stock excess return, VIX volatility premium, term premium, changes in 5-year treasure rates, investment grade spread and high yield premium. Local risk variables contain the local exchange rate return, local equity risk return. Sovereign spreads are the global sovereign spreads and regional sovereign spreads. The sample period spans from January 2003 to April 2014 at weekly frequency. *** stands for 1% significant level; ** stands for 5% significant level; * stands for 10% significant level.

	BGARIA	**BRAZIL**	**CHILE**	**CHINA**	**COLOM**	**CROATI**	**ISRAEL**
Global risk factors							
US stock market	-0.009***	-0.010***	-0.005*	-0.003	-0.012***	-0.009***	-0.003
Volatility premium	-0.001**	-0.002***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
Term premium	0.001	-0.000	0.000	0.003***	-0.000	0.000	0.002**
Treasury market	0.100***	0.219***	0.071**	0.155***	0.218***	0.077***	0.061***
Investment grade	-0.005***	-0.003***	-0.003**	-0.004*	-0.003***	-0.005**	-0.002
High yield	1.573***	1.216***	1.572***	1.453***	1.411***	1.508***	0.931***
Local variables							
Exchange return	-0.155	-0.375***	0.320	-0.316	-0.065	0.082	-0.246
Stock return	0.091	-0.198***	-0.172	0.012	-0.093	0.046	0.068
Sovereign spreads							
Regional spread	0.053	0.117	0.283**	0.276*	0.148*	0.083	0.343***
Global spread	0.899***	0.976***	0.442***	0.947***	1.024***	0.848***	0.365***
Global news sentiment	-0.081***	-0.094***	-0.125***	-0.108***	-0.115***	-0.108***	-0.067***
Constant	0.007**	0.004	0.008**	0.007	0.003	0.008**	0.001
N	448	568	568	568	568	568	568
Adjusted R^2	0.776	0.888	0.585	0.768	0.890	0.745	0.575

Table B.6. Regression Results with Global News: CDS^Q return (Continue)

	JAPAN	KOREA	MALAYS	MEX	PANAMA	PHILIP	POLAND
Global risk factors							
US stock market	-0.001	0.004	-0.000	-0.009***	-0.008***	-0.002	-0.007**
Volatility premium	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
Term premium	-0.002	0.003*	0.003**	0.001**	0.001	0.001**	0.001*
Treasury market	0.103**	0.130***	0.121***	0.189***	0.186***	0.119***	0.088***
Investment grade	-0.004	-0.006***	-0.005***	-0.005***	-0.002***	-0.002*	-0.005***
High yield	1.075***	1.535***	1.374***	1.456***	1.497***	0.945***	1.605***
Local variables							
Exchange return	0.448	-0.359	-0.533	-0.854***		-1.239***	-0.326**
Stock return	-0.283	-0.009	-0.194	0.010	-0.192**	-0.302***	-0.106
Sovereign spreads							
Regional spread	0.422***	-0.077	-0.038	0.064	0.022	0.274***	0.075
Global spread	0.046	1.052***	1.096***	0.949***	1.015***	0.419***	0.926***
Global news sentiment	-0.125***	-0.115***	-0.053**	-0.100***	-0.085***	-0.053***	-0.080***
Constant	0.007	0.005	0.002	0.004	0.004	-0.001	0.006*
N	568	568	568	568	257	568	568
Adjusted R^2	0.364	0.699	0.782	0.840	0.921	0.754	0.703

	QATAR	ROMANI	RUSSIA	SLOVAK	SOAF	UKRAIN	VENZ
Global risk factors							
US stock market	-0.000	-0.006*	-0.007	-0.003	-0.006	-0.007**	-0.007**
Volatility premium	-0.002***	-0.001**	-0.001	-0.004***	-0.002***	-0.000	-0.001
Term premium	0.000	0.001	0.000	0.003	0.002**	0.001	-0.000
Treasury market	0.079***	0.055**	0.150***	0.045	0.153***	0.079**	0.126***
Investment grade	0.001	-0.005***	-0.003*	-0.002**	-0.005***	0.000	-0.002
High yield	0.991***	1.446***	1.498***	1.441***	1.404***	1.315***	0.979***
Local variables							
Exchange return	0.491	-0.282*	-0.317	-0.075	-0.345**	-0.016	0.043
Stock return	-0.163*	0.022	-0.367**	-0.150	0.156	-0.238***	-0.196**
Sovereign spreads							
Regional spread	0.394***	-0.120*	0.278	0.203	0.803***	0.272***	0.099
Global spread	0.224**	0.922***	0.496***	0.873***	0.078	0.323***	0.525***
Global news sentiment	-0.113***	-0.050*	-0.089*	-0.174***	-0.078*	-0.100**	-0.094***
Constant	0.006*	0.006*	0.007	0.001	0.004	0.011**	0.009**
N	448	422	568	283	568	397	568
Adjusted R^2	0.560	0.781	0.660	0.751	0.670	0.578	0.509

B.2 Variables Construction

US stock market is the excess return for the U.S. stock market, which is the daily value-weighted return on all NYSE, AMEX, and NASDAQ stocks from CRSP in excess of Treasury bill return (from Ibbotson Associates). Data is downloaded from the Kenneth French website.[1]

Volatility premium is daily VIX index minus the 30 days realized volatility of the S& P 500 index. Both time series are obtained from Bloomberg.

Term premium is calculated as the difference between the 10-year USD Interest Rate Swap rate and the 1-month USD Libor rates. Both time series are obtained from Bloomberg.

Treasury market is the changes in the 5-year treasury rate of the United States. The data is downloaded from Bloomberg.

Investment grade is the daily return on the basis point yield between the Bank of America/ Merrill Lynch US Corporate BBB Effective Yield and the corresponding Corporate AAA Effective Yield. The data is downloaded from the Federal Reserve Bank of St. Louis.

High yield is the daily return on basis points spread difference between the Bank of America/Merrill Lynch US High Yield BB and the corresponding Corporate BBB Effective yield. The data is downloaded from the Federal Reserve Bank of St. Louis.

Funding premium is calculated as the difference between the 3-month Libor rate and the OIS rates of US Dollar. Both time series are obtained from Bloomberg.

Exchange return is defined as the return of the exchange rate, which is expressed as units of the local currency per US dollar. The data is obtained from the Bloomberg and Datastream.[2]

Stock return is calculated as the rate of return for local MSCI equity index. The data is download from the same source. The data is obtained from the Bloomberg and Datastream.

[1] http://mba.tuck.dartmouth.edu /pages/faculty/ken.french/date_library.html.

[2] The exchange rate against USD for the Panama stays constant over the period, the return is set as zero over the period and the variable is omitted in the regression.