Information Content of Credit Default Swaps: Price Discovery, Risk Transmission, and News Impact

SHI, SHIMENG

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By

Shimeng Shi

Department of Economics and Finance

Durham University Business School

Durham University

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Shimeng Shi

Abstract

This thesis comprises three empirical studies regarding information content of credit default swap (CDS). The first study provides further evidence of credit risk discovery between CDS and stock of the U.S. non-financial firms. Stock generally leads CDS in discovering credit risk information, with the exception of the stressful financial crisis period of 2008–2010. The CDS of investment-grade firms generally possesses higher informational efficiency than that of speculative-grade firms. High funding cost and central clearing counterparty hinder CDS from rapidly incorporating credit risk news.

The second study investigates dynamics and determinates of credit risk transmission across the global systemically important financial institutions (G-SIFIs). The aggregate credit risk transmission across G-SIFIs dramatically increases from mid-2006 to mid-2008 and then fluctuates around 90% until 2014. Global systemically important banks (G-SIBs) and the U.S.–based G-SIFIs are major credit risk providers. More interbank loans, more non-banking income, higher extra loss absorbency requirement, and lower Tier 1 leverage ratio are positively related to a G-SIB's role in credit risk transmission. Global systemically important insurers (G-SIIs) which have more non-traditional non-insurance activities, larger sizes, and more global sales tend to be credit risk senders.

The final study examines the impact of sovereign credit rating and bailout events on sovereign CDS and equity index, especially their contemporaneous correlation, in the U.S., the U.K., and the Eurozone countries. The two assets are less negatively correlated at the arrivals of domestic rating events or surprises. Good and bad rating events present

asymmetric effects on the asset correlation in Portugal, Netherlands, Ireland, Finland, and the U.S., while their symmetric effects are found in Spain, Italy, and Cyprus. Two assets become more negatively correlated on the announcement days of major bailouts. Bailout events have a stronger impact than domestic rating events. Greek rating news exerts spillover effect and generally has positive impact on the asset correlation in other economies.

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List of Abbreviations

ADCC-X	Asymmetric Dynamic Conditional Correlation Model with Exogenous Variables
ADF	Augmented Dickey-Fuller Unit Root Test
BCBS	Basel Committee on Banking Supervision
BFCIUS	Bloomberg Financial Condition Index
BIS	Bank for International Settlements
CCP	Central Clearing Counterparty
CCR	Comprehensive Credit Rating
CDS	Credit Default Swap
CET1	Common Equity Tier 1 Capital Ratio
CME	Chicago Mercantile Exchange
CoVaR	Conditional Value-at-Risk
CR	Complete Restructuring
CRC	Credit Risk Connectedness
CS	CDS Spread
CW-Dev/Pos/Neg	Credit Watch – Developing/Positive/Negative
DIP	Distressed Insurance Premium
ECB	European Central Bank
ECR	Explicit Credit Rating
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EFSF	European Financial Stability Facility
EFSM	European Financial Stabilisation Mechanism
ESM	European Stability Mechanism
FC	Funding Cost
FEVD	Variance Decomposition of Forecast Errors
FINRA	Financial Industry Regulatory Authority
FSB	Financial Stability Board
GCA	Generalised Contribution Approach
GDP	Gross Domestic Product
GG	Component Share
GIIPS	Greece, Italy, Ireland, Portugal, and Spain
GIS	Generalized Information Share
GLS	Generalized Least Squares
G-SIFIs	Global Symmetrically Important Financial Institutions
G-SIBs	Global Symmetrically Important Banks
G-SIIs	Global Symmetrically Important Insurers
GSFCI	Goldman Sachs Financial Condition Index
GMM	Generalise Method of Moments
GVD	Generalised Variance Decomposition
IAIS	International Association of Insurance Supervisors
ICE	Intercontinental Exchange
ICS	Implied Credit Spread
IMF	International Monetary Fund
IOSCO	International Organization of Securities Commissions
IS	Information Share

ISDA	International Swaps and Derivatives Association
LCS	CS obtained from the permanent price component after eliminating transitory components
LICS	ICS obtained from the permanent price component after eliminating transitory components
LP	Permanent Price Component
MES	Marginal Expected Shortfall
MM	Modified Modified Restructuring
NTNI	Non-Traditional Non-Insurance
OLS	Ordinary Least Squares
OTC	Over-the-Counter
PA	Participation Approach
PCA	Principal Component Analysis
SBC	Schwarz Information Criterion
SD	Standard Deviation
SD/RD/D	Selective Default/ Restricted Default/ Default
SRISK	Systemic Risk Measure
SS	Spillover Score
XR	No Restructuring
VAR	Vector Autoregression
VaR	Value-at-Risk
VECM	Vector Error Correction Model
Z_{CRC}	Scored Credit Risk Connectedness

Statement of Copyright

No part of this thesis has been submitted elsewhere for any other degree or qualification in this or any other university. It is all my own work unless referenced to the contrary in the text.

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Chapter 1: Introduction

1.1 Informational Role of Credit Default Swap

The derivatives markets, such as futures, options, and swaps, provide alternative venues for risk management and information-based trading (e.g., Garbade and Silber, 1983; Fleming et al., 1996; Easley et al., 1998; Longstaff et al., 2003). Therefore, one of the main economic functions of the derivatives markets is producing information (Stulz, 2004). To be specific, the derivatives provide price discovery. Price discovery refers to the process of how the new information related to the fundamental value of one security gets incorporated into the relevant markets (Hasbrouck, 1995). Given that the central question of price discovery has several dimensions, one may address this question from different perspectives (Andersen et al., 2007). For instance, how quickly do asset prices incorporate news? Is the impact of news on returns and volatility different across assets, and whether the interrelations across assets are also affected by the news? Besides price discovery, as the promised payoffs of the derivatives are mainly depend on the value of the underlying asset, the derivatives also provide information regarding the underlying asset. For example, it is argued that credit derivatives offer a simple and straightforward measure of default risk of the underlying reference entity (Chiaramonte and Casu, 2013).

Credit default swap (CDS) is an important credit derivatives. It provides insurance to investors who own defaultable bonds or other risky fixed-income securities issued by one or more reference entities. In a predetermined credit event, the CDS seller agrees to either repay an obligation of the reference entity underlying the contract at par in the case of physical settlement or pay the difference between par value and the market price of the obligation in the case of cash settlement. To purchase this protection, the CDS buyer pays a regular premium during a specified period. This premium is referred to as

CDS spread and denominated in basis points. CDS spread is calculated by equating the present value of the protection leg (protection seller) with the present value of the premium leg (protection buyer) (Markit, 2008). As an important credit derivatives, CDS is expected to produce credit risk information via contributing to credit risk discovery and indicating default risk of the underlying reference entity (Stulz, 2010). Therefore, the general motivation and focus of this thesis is to investigate several issues with regard to the informational role of CDS in capturing credit risk news and in directly indicating market expectation of the default risk of the underlying reference entity.

1.2 Institutional Background of the Credit Default Swap Market

Based on the number of the underlying reference entities, CDS contracts are classified as single-name instruments, multi-name instruments, and index products. In December 2015, the notional amounts outstanding, in billions of U.S. dollars, of the three products are 7,183, 5,110, and 4,737, respectively (BIS, 2016). Since single-name instruments have relatively large notional value and attract increasing attention from the academia, this thesis focuses only on single-name CDS contracts. Based on the characteristics of the underlying reference entities, the single-name CDS products are further divided into three types: the CDS contracts for non-financial firms, for financial institutions, and for sovereigns. In contrast with corporate CDS contracts (including both non-financial and financial companies), sovereign CDS contracts have different natures of credit events, less concentrated trading in the 5-year maturity, higher currency risk, and the capacity to hedge country default risk exposures of portfolios (Augustin et al., 2014). Figure 1.1 presents the proportions of the notional amounts outstanding of three categories of single-name CDS instruments during the period of 2004–2015. The figure indicates that the single-name CDS contracts for non-financial firms have the highest notional value, followed by that for financial institutions and sovereigns.

According to the European Commission (2011), market participants in the CDS market consist of dealers, non-dealer banks, hedge funds, and asset managers. The dealers are by far the major players in the market. Market participants engage in the CDS market for three main purposes. First, they use CDS for hedging. For example, bondholders are exposed to the default risk of the bond issuers; therefore, they use CDS to transfer the credit risk to the CDS sellers. Second, CDS is used for arbitrage. Capital structure arbitrage and CDS-bond basis arbitrage strategies are employed largely by hedge funds to earn risk-free profits. The final purpose is speculation, when investors exploit price changes by trading CDS in and out. Overall, the CDS market offers market participants an additional venue to manage credit risk and generate profits.

However, many questions have been raised about the CDS market, especially during the recent financial crises. For example, Acharya and Johnson (2007) uncover insider trading issue in the CDS market. Cecchetti et al. (2009) criticise the opacity of its over-the-counter (OTC) market structure and the abuse of CDS contracts by large financial institutions. The speculations with uncovered sovereign CDS positions are accused of exacerbating the European sovereign debt crisis (Pu and Zhang, 2012).[1] Owing to the controversy related to the CDS market, stricter regulations are imposed on this OTC derivatives market. For example, the International Swaps and Derivatives Association (ISDA) initiated a CDS 'Big Bang' Protocol and implemented it in April, 2009. The Big Bang Protocol standardises CDS contracts to benefit compression mechanisms and the development of central clearing counterparty (CCP). Moreover, to facilitate CDS contract settlements, ISDA, Markit, and CreditEx jointly designed and administered a CDS auction process (Augustin et al., 2014). Also, as encouraged by regulators, CDS

[1] As explained by the European Commission (2011), an uncovered or naked CDS position is taking a CDS position without owning the underlying securities.

contracts should be traded through CCP to improve market transparency and reduce counterparty risk. Figure 1.2 presents the ratios of the notional amounts outstanding of single-name CDS contracts cleared by CCP to that traded by all types of counterparties from 2010 to 2015. The figure shows that settling CDS positions through CCP has been a trend. Compared with financial institutions and sovereigns, a higher percentage of non-financial companies' CDS contracts is centrally cleared. In addition, in Europe, to curb the deterioration of the sovereign debt crisis, a permanent short-selling ban on 'naked' sovereign CDS contracts was enacted in 2011. Table 1.1 presents a timeline of the major developments in the CDS market from 1994 to 2016. The CDS market can be considered as an attractive laboratory for investigating the impact of new regulatory policies on its market transparency, liquidity, and counterparty risk, see, e.g., Duffie and Zhu (2011), Slive et al. (2012), and Loon and Zhang (2014).

1.3 Objectives

Based on the general motivation mentioned in Section 1.1 and the three products of the single-name CDS market introduced in Section 1.2, this thesis examines three different, but interrelated, topics regarding informational content of single-name CDS contracts. Chapter 2 studies credit risk discovery function of CDS and stock of the U.S. non-financial firms. Chapter 3 employs CDS spread as default risk proxy to investigate credit risk transmission across the global systemically important financial institutions. Chapter 4 examines the impact of sovereign rating and bailout events on sovereign CDS and equity index in major developed economies.

1.3.1 Credit Risk Discovery of Non-Financial Corporate CDS

Recently, a stream of literature related to credit risk discovery has emerged. Credit risk discovery analysis involves credit risk sensitive assets, such as CDS, bond, stock, and stock option. Given structural differences of markets and various trading purposes of market participants, prices of credit risk sensitive assets are not likely to simultaneously respond to news (Norden and Weber, 2009). Accordingly, it is a key interest to identify which market incorporates new credit risk information more promptly than the others, so that investors can receive an early warning on impending and possible large changes of asset prices and policymakers can monitor and assess information spillovers across markets (Avino et al., 2013). However, compared with the price discovery literature related to internationally or domestically cross-listed stocks, e.g., Eun and Sabherwal (2003), and derivatives with underlying assets, e.g., So and Tse (2004), credit risk discovery has not been fully explored.

Previous credit risk discovery research tries to address the question of which credit risk sensitive asset firstly incorporates credit risk news. It seems to be a consensus that CDS leads bond in credit risk discovery. For instance, Blanco et al. (2005) find that in contrast to bond, CDS contributes about 80% of price discovery. Similar conclusions are drawn in other works, e.g., Longstaff et al. (2003), Zhu (2006), and Forte and Peña (2009). In terms of the relationship between CDS and equity option, Avino et al. (2013) document that option dominants CDS in the sub-prime crisis (2007–2009), while during the European sovereign debt crisis (2009–2012) and the pre-crisis period, CDS leads option. Berndt and Ostrovnaya (2014) find bidirectional information flows between CDS and equity option markets and detect that information in option trading volumes, especially the put option, spills over to the CDS market.

Regarding the credit risk discovery relationship between CDS and stock, mixed results are obtained–for example, Longstaff et al. (2003), Norden and Weber (2009), and Xiang et al. (2013)–and several research gaps exist. Hence, further research is necessary. First, prior studies use traditional price discovery contribution measures, that is, Hasbrouck's

(1995) information share (IS) and Gonzalo and Granger's (1995) component share (GG). However, these measures have drawbacks, such as non-uniqueness and/or the one-to-one cointegration restriction. Generalised Information Share (GIS) proposed by Lien and Shrestha (2014) is a unique measure and relaxes the one-to-one cointegration assumption. Due to different market structures and various levels of market frictions that limit arbitrage activities, credit risk proxies of CDS and stock markets may not be one-to-one cointegrated in the long run. Therefore, GIS is a more suitable measure for studying credit risk discovery between CDS and stock markets. Also, in the U.S. market, the question of whether transitory components in CDS spreads and stock prices, such as liquidity risk, would affect credit risk discovery process has not been answered. In addition, the determinants of credit risk discovery leadership between CDS and stock are not well investigated. Although Forte and Lovreta (2015) propose several factors, e.g., market liquidity, reference entity's credit condition, and adverse shocks, the impact of the funding cost and the newly introduced CCP on the informational efficiency of CDS and stock markets is unknown. Hence, the objectives of Chapter 2 are providing further evidence about credit risk discovery between CDS and stock markets of the U.S. non-financial firms and proposing new determinants of the credit risk discovery process.

1.3.2 Credit Risk Connectedness of Systemically Important Financial Firms

The failures of major financial institutions and the following global financial crisis in late 2008 have made it necessary to regulate the large and closely interrelated financial institutions. A widespread regulatory consensus has emerged among governments and central banks that ad-hoc bailouts of financial companies (as in the case of the bailout of AIG) should not be the way forward and that no individual bank or insurer should be 'too-interconnected-to-fail'. Since 2010, the Financial Stability Board (FSB) has formally identified and released two lists of financial institutions that are considered as systemically important to the global economy (G-SIFIs) in the sense that the failure of one of them may trigger contagious defaults in the whole financial system, i.e., global systemically important banks (G-SIBs) and global systemically important insurers (G-SIIs). More intensive regulations and extra capital surcharges have since been imposed on these G-SIFIs to ensure that these G-SIFIs are less likely to disorderly default with an adverse impact on other financial institutions. Since the releases of the lists of G-SIFIs, policymakers, academics, and practitioners have devoted time to measure their systemic importance and financial connectedness. While the financial linkages among financial institutions may not always pose devastating effects on financial stability, it is critical to identify which financial company poses the most credit risk to the financial system and understand when the dependency across financial firms would impair the health of the financial sector and subsequently disrupt the real economy.

There are several streams of growing literature associated with G-SIFIs. For instance, different approaches are proposed to define systemic risk and identify potential G-SIFIs, which can complement the current indicator-based methodology designed by the Basel Committee on Banking Supervision (BCBS) (2013) and the International Association of Insurance Supervisors (IAIS) (2013) (e.g., Yang and Zhou, 2013; Castro and Ferrari, 2014). Also, applying event study method, several papers compare stock and/or CDS reactions of G-SIFIs with that of large financial institutions which are not deemed to be systemically important to the news announcements related to G-SIFIs (e.g., Abreu and Gulamhussen, 2013; Bongini et al., 2015). Moreover, returns and volatility spillovers among G-SIFIs' stock prices are studied, as well as the dependent structures between CDS indices and G-SIFIs' stock prices (e.g., Elyasiani et al., 2015; Calice, 2014).

Furthermore, using default risk information provided by CDS market data, Billio et al. (2013) and Yang and Zhou (2013) have presented the first attempt to analyse credit risk transmission across financial firms. However, these studies either track only pairwise interconnection or do not monitor the time-varying credit risk spillovers across financial institutions. Although several papers have examined factors affecting financial firms' systemic importance or risk spillovers (e.g., Yang and Zhou, 2013; Bierth et al., 2015), they either use systemic risk measures calculated by using stock market data or omit several important factors. Therefore, Chapter 3 is motivated to employ CDS market data and the VECM-based connectedness measures of Diebold and Yilmaz (2015a) to investigate the dynamic credit risk transmission across the designated G-SIFIs. CDS market data have been argued to be better than stock market data in analysing financial firms' systemic importance since CDS spread can be considered as a direct and simple indicator of default probability of financial institution (e.g., Chiaramonte and Casu, 2013; Rodríguez-Moreno and Peña, 2013; Acharya et al., 2017). Complementing the existing market-based systemic risk indicators, e.g., Billio et al.'s (2012) connectedness measures, Diebold and Yilmaz's (2015a) approach not only allows for cointegration relations shared by default risk of financial institutions, but also provides diverse types of directed and weighted connectedness matrices, from firm-level pairwise directional measures to system-wide aggregate measures. In addition, we suggest an approach to complement the indicator-based methodology used by the FSB to identify the potential G-SIFIs. Additionally, this chapter examines the possible factors that explain credit risk connectedness across the G-SIFIs.

1.3.3 Credit Risk News Impact on Sovereign CDS and Equity Index

In early May 2010, the unsustainable Greek sovereign debt was on the brink of imminent default. Due to significant holdings in Greek sovereign debt, the European governments and financial institutions also suffered from financial troubles and faced higher risk of default. Hence, the 'Greek crisis' rapidly propagated throughout Europe.

Since the European sovereign debt crisis, default risk of the developed economies has become a major concern of academics, policymakers, and international investors. Thus, after investigating two issues associated with the information content of corporate (non-financial and financial firms) CDS in Chapter 2 and Chapter 3, Chapter 4 focuses on studying the informational role of sovereign CDS in reacting to sovereign default risk news in major advanced countries.

The assets sensitive to sovereign default risk include, but are not limited to, sovereign CDS, equity index, government bond, and exchange rate and its derivatives. Carr and Wu (2007) and Hui and Fong (2015) examine dynamic interrelations and cointegration relationships between sovereign CDS and currency option, respectively. Ammer and Cai (2011) and Fontana and Scheicher (2016) discuss the relations between sovereign CDS and government bond in emerging markets and developed Eurozone countries, respectively. Sovereign CDS and equity index are linked by a country's sovereign credit risk (Ngene et al., 2014). On the one hand, sovereign CDS spread offers compensation to investors for assuming sovereign credit risk. Hence, it is directly driven by sovereign default risk. On the other hand, sovereign credit risk and equity market are exposed to common economic shocks (Jeanneret, 2017), and information delivered by sovereign default risk influences equity market via at least three channels: a) economic prospects (Jeanneret, 2017); b) corporate borrowing costs (Bedendo and Colla, 2015); c) investors' portfolio rebalancing (Hooper et al., 2008). A few researchers study the relationship of these two markets in terms of sovereign default risk pricing (e.g., Chan-Lau and Kim, 2004), lead-lag relation in discovering sovereign credit risk news (e.g., Ngene et al., 2014), and possible cross-asset arbitrage and hedge activities (e.g., Chan et al., 2009). However, limited studies examine the contemporaneous correlation of the two assets. Asset correlation is critically important for policymakers to monitor risk contagion and for international investors to manage portfolios and control risk (Karolyi and Stulz, 1996; Fleming et al., 1998). In this regard, Chapter 4 aims to measure the correlation of sovereign CDS and equity index in the U.S., the U.K., and the states in the euro area.

According to Andersen et al. (2007), besides examine the lead-lag relationships across assets, one may address the central price-discovery question from the perspectives of studying whether the impact of news on returns and volatility is different across assets and whether the links of assets are also affected by news. A strand of literature discusses the news impact on assets and asset correlations. For example, using a modified Engle's (2002) GARCH-DCC model, Brenner et al. (2009) analyse how macroeconomic news surprises affect the conditional mean, volatility, and covariance of the U.S. stock, government bond, and corporate bond markets. They find that the comovement across assets changes around the arrival of the U.S. macroeconomic news. They explain that when macro news is announced, cross-asset trading activities caused by information transmission (e.g., Karolyi and Stulz, 1996), wealth effects (e.g., Kyle and Xiong, 2001), portfolio rebalancing (e.g., Fleming et al., 1998), and raised dispersion of expectations among investors (e.g., Kallberg and Pasquariello, 2008) may explain the changes of the comovement across assets. Using diagonal tail-dependence coefficients, Chui and Yang (2012) find that besides the U.S. macroeconomic news, stock market uncertainties and business cycle significantly affect the correlation of stock–bond futures in the U.S., the U.K., and Germany. While several papers have separately studied the impact of macro news on sovereign CDS and equity index, limited studies have addressed the question of whether their correlation can be driven by such news or it simply indicates the general linear relationship between them. By using asymmetric dynamic conditional correlation model with exogenous variables (ADCC-X), Chapter 4 not only takes into account the impact of macro news releases on returns and volatility of sovereign CDS and equity index, but also provides evidence of the news impact on their correlation.

Among a wide range of macro news, Chapter 4 concentrates on two events related to sovereign default risk, that is, sovereign credit rating changes and bailouts. Sovereign credit ratings reflect the capacity and willingness of sovereigns to fulfil debt obligations and are mainly determined by one country's economic circumstance, default record, and political risk, and they are crucial inputs of evaluating investment opportunities (Christopher et al., 2012). Regarding bailouts, during the global financial crisis, the U.S. and the U.K. authorities provided bailouts to the distressed banking sector or financial institutions to stabilise the financial system. According to Acharya et al.'s (2014) 'two-way feedback' model, the bailouts of the domestic financial sectors could induce credit risk transfer from the private sector to the public sector, so that sovereign default risk is more likely to increase. In the Eurozone, the European Financial Stability Facility (EFSF), the European Financial Stabilisation Mechanism (EFSM), and the European Stability Mechanism (ESM) were created to relieve the sovereign debt crisis and save the indebted Eurozone members from bankruptcy. These stabilisation mechanisms and the International Monetary Fund issued large scale of funding to Greece, Ireland, Portugal, Spain, and Cyprus. As a result, the probabilities of default of these five sovereigns are expected to be lower. However, as the guarantors of the funding facilities, the rest of the Eurozone members have to share the financial burden of those indebted states and their sovereign credit risk may be adversely affected. Since the bailouts of the domestic financial institutions or the bailouts of indebted Eurozone states could exert effects on sovereign credit risk of relevant countries, the financial markets in these economies are expected to be affected by the bailout news. In sum, Chapter 4 aims to provide further empirical evidence with regard to the impact of sovereign credit rating and bailout events on sovereign CDS and equity markets in major advanced economies.

1.4 Major Findings and Contributions

Employing generalised information share (GIS) of Lien and Shrestha (2014), Chapter 2 addresses the issue that CDS spread and stock implied credit spread may not have a one-to-one cointegration relation required by Hasbrouck's (1995) information share (IS) and Gonzalo and Granger's (1995) component share (GG). Nevertheless, all the three measures provide qualitatively similar empirical results. The stock market generally leads the CDS market in capturing credit risk news, except for the period of 2008–2010. Eliminating transitory price components, such as the liquidity effect, increases the informational efficiency of the CDS market in the earlier period of the sample. Another finding is that the CDS of investment-grade firms contributes more to credit risk discovery compared with that of speculative-grade firms. Further, the overall economy condition and funding cost negatively affect the credit risk discovery contribution of the CDS market. Finally, CCP seems to hinder CDS from capturing credit risk news first, which supports that the CDS market may be driven largely by insider trading.

Chapter 2 contributes to the existing literature in the following aspects. First, while GIS technique may be theoretically stronger than IS and GG methods, our findings suggest that it does not make material difference in the relative price discovery contribution of CDS contracts. Second, this chapter provides support to several previous papers which demonstrate the general dominant role of the stock market in credit risk discovery, e.g., Forte and Peña (2009) and Narayan et al. (2014). However, during the period of 2008–2010, the CDS market is found to dominate the stock market, which supports Xiang et al. (2013). Third, the current understanding of the impact of eliminating transitory components on credit risk discovery is extended. This chapter finds that for the U.S. firms, the impact is generally insubstantial but time-varying, complementing Forte and Lovreta's (2015) study. By suggesting new factors, it adds to the extant literature of the drivers of the informational efficiency of CDS and stock markets. The negative effects of funding cost and central clearing service on the market efficiency of the CDS market may help investors to design better trading strategies and benefit regulators in terms of effectively regulating the CDS market.

Using Diebold and Yilmaz's (2015a) VECM-based connectedness measures, Chapter 3 finds a significant rise in the total credit risk transmission among the G-SIFIs during the period of severe financial events; as the financial crises intensified, so too did the cross-border spillovers of default risk, with a significant threat carrying over from the large U.S. banks and insurers to the other G-SIFIs in the EU and Asia. While there are bilateral linkages between G-SIBs and G-SIIs, the threat to the global financial stability that a large bank would pose if it were to fail is generally greater than that of an insurer. The changes in interbank lending, unconventional banking activity, regulatory leverage ratio, and extra loss absorbency requirement can have a significant impact on a G-SIB's role in credit risk transmission. A G-SII's role in credit risk spillovers can be positively determined by its non-traditional non-insurance activity, size, and global business.

Chapter 3 adds to the literature in a number of aspects. Firstly, it improves the current understanding of credit risk transmission across financial firms, e.g., Yang and Zhou (2013), by focusing on the G-SIFIs identified by the FSB. Second, unlike Diebold and Yilmaz (2015a), this chapter suggests that the empirical findings of VECM model and that of VAR model are qualitatively similar. It implies that although VECM model is econometrically more robust than VAR model as it allows for possible cointegration relations shared by the G-SIFIs' credit risk, it may not necessarily provide substantially different empirical results. Third, this study adds to the existing literature of systemic importance of each financial firm by proposing a ‘too-interconnected-to-fail’ ranking to identify which G-SIFI is the major credit risk provider or receiver. Since this ranking is derived directly from CDS market data, it is complementary to the FSB’s list that is based on accounting data. Regulators may combine the two lists to obtain a ‘composite’ ranking that considers diverse sources of information. Finally, it offers further evidence of the drivers of credit risk spillovers of financial institutions, which complements the extant literature, e.g., Yang and Zhou (2013). The findings of regulatory leverage ratio and extra loss absorbency requirement may help regulators improve regulation in terms of curbing the G-SIBs to be more systemically important.

Using asymmetric dynamic conditional correlation model with exogenous variables (ADCC-X), Chapter 4 finds that in contrast with equity market, sovereign CDS market is more sensitive to domestic sovereign rating events or surprises. The arrivals of rating events/surprises are accompanied with an increase of the negative correlation of the two assets. Both symmetric and asymmetric reactions of returns and volatility of two assets to positive and negative rating news are found. Two rating events symmetrically affect the negative asset correlation in Spain, Italy, and Cyprus, while they exert asymmetric influence on the correlation in Portugal, Ireland, Netherlands, Finland, and the United States. Bailout news is accompanied by wider CDS spreads and worse equity market performance. Asset volatility increases and two assets are more correlated. Compared with domestic sovereign rating events, bailout news has stronger and more significant influence on individual assets as well as asset correlation. Greek rating events generate spillover effect on sovereign CDS and equity markets in several sample countries. The two assets becomes less negatively correlated when Greek rating events occur.

Chapter 4 contributes to the existing literature on several dimensions. First, this chapter adopts a more general measure to define sovereign credit rating events and it calculates rating surprises, which complements the existing methods used by Gande and Parsley (2005) and Drago and Gallo (2016). Second, it adds to the existing literature relating macro news to the returns and volatility of different assets as well as the correlation between assets, such as Andersen et al. (2007) and Brenner et al. (2009). It finds that the conditional correlation of sovereign CDS and equity index is not a simple indicator of their relationship, but can be driven by the releases of sovereign credit rating and bailout events. Brenner et al. (2009) suggest that the changes of asset correlation on the announcement days of macro news may be attributable to any cross-asset trading which is jointly induced by information spillovers, portfolio rebalancing, wealth effects, and increased degree of disagreement among investors. Moreover, bailout news exerts more significant impact. Finally, it extends the current understanding of the spillover effect of sovereign rating events, e.g., Ismailescu and Kazemi (2010), by showing that Greek sovereign rating news can affect not only the returns and volatility of two assets, but also their correlation in several sample countries.

1.5 Structure of the Thesis

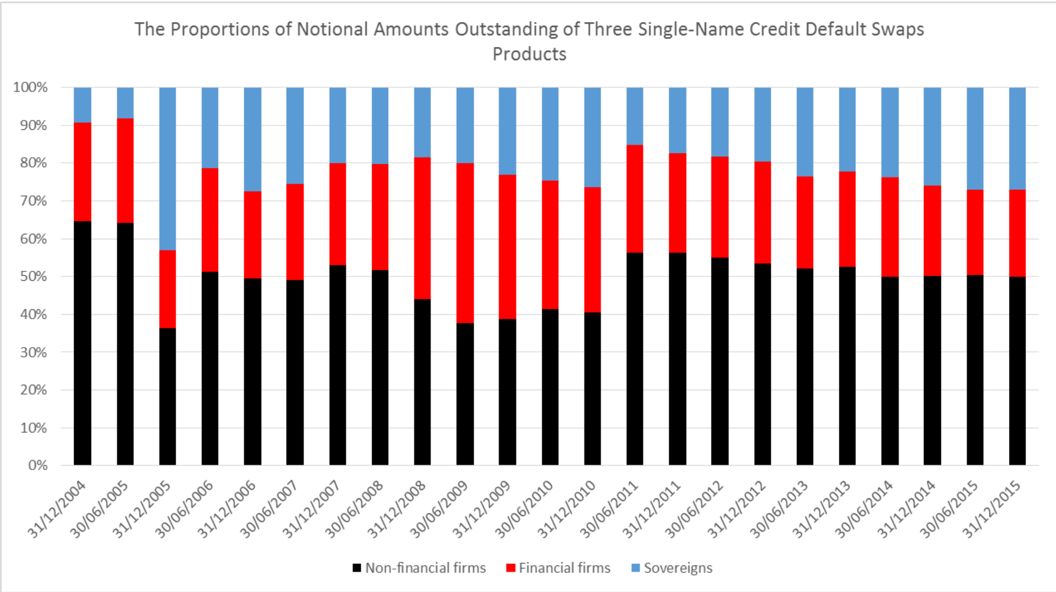
The remainder of this thesis is organised as follows. Chapter 2 analyses the dynamics and drivers of credit risk discovery of CDS and stock of the U.S. non-financial firms. Chapter 3 investigates the time variations and determinants of credit risk connectedness across multinational systemically important financial institutions. Chapter 4 examines the influence of sovereign credit rating and bailout news on sovereign CDS and equity index in the U.S., the U.K., and the Eurozone countries. Chapter 5 summaries the three empirical studies and indicates the limitations of the thesis and further research. The tables, figures, and appendices are presented at the end of each chapter.

Table 1.1: Timeline of the CDS Market Development

1994	CDS was created by JP Morgan
1999	ISDA published the Credit Derivatives Definitions
2000	CDS and other derivatives were exempted from regulation, according to the Commodity Futures Modernization Act of 2000
2001	ISDA published Restructuring Supplement to the 1999 Credit Derivatives Definitions
2003	ISDA updated the 1999 Credit Derivatives Definitions
2004	CDS index was introduced
2005	General Motors/ Ford Motor was downgraded; Delphi defaulted
2006	Loan credit default swap (LCDS) was introduced
2007	Loan credit default swap index (LCDSX) was launched
2008	AIG was downgraded; Ecuador defaulted
2009	ISDA published 'Big Bang' and 'Small Bang' protocols; central clearing operations (CCP) began
2010	More CDS position and trading volume data are available at the Depository Trust & Clearing Corporation (DTCC); The Dodd-Frank Act set regulatory framework; Germany banned the naked (uncovered) short-selling of CDS written on euro-denominated government bonds
2011	The European regulators enacted permanent short-selling ban on naked (uncovered) sovereign CDS contracts
2012	JP Morgan suffered from large losses because of CDS trading, which is referred to as 'London Whale'; Greece defaulted
2013	Mandatory central clearing of eligible CDS indices commenced
2014	ISDA updated the 2003 Credit Derivatives Definitions; Deutsche Bank AG stopped trading most single-name CDS contracts
2015	BlackRock discussed with banks and other debt investors to revive the credit derivatives trading, especially the single-name CDS contracts
2016	Due to a rise of downgrades and defaults of firms, China launches CDS market to provide investors an alternative venue to hedge credit risk

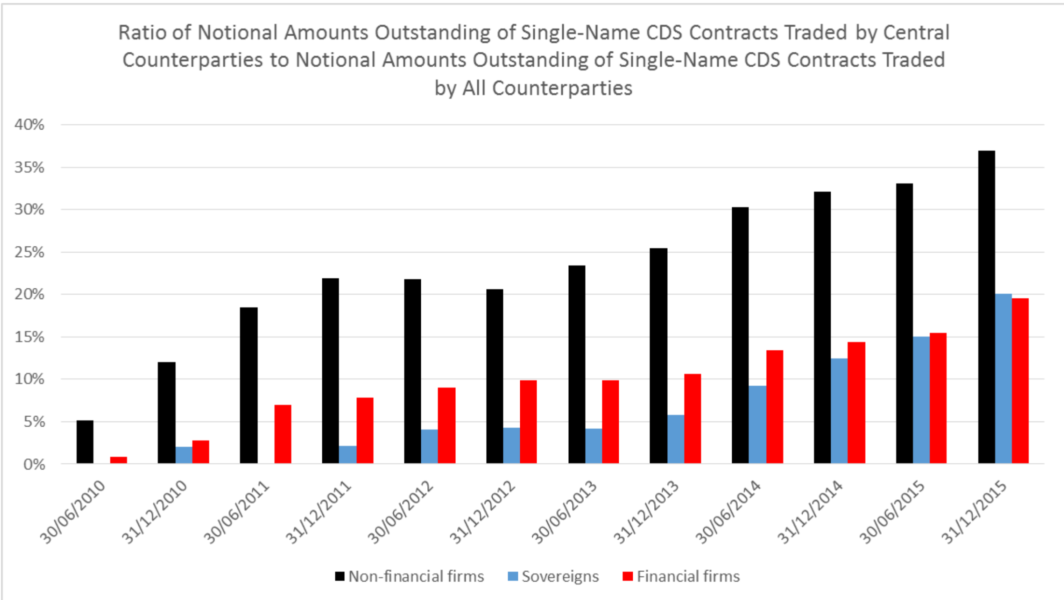
Notes: This table briefly summaries the key developments in the global CDS market. Sources: Augustin et al. (2014), the ISDA, and Bloomberg.

Figure 1.1: Notional Amounts Outstanding of Single-Name CDS Contracts



Notes: This figure reports the proportions of the national amounts outstanding of three single-name CDS products, that is, CDS for non-financial firms, for financial firms, and for sovereigns. Data sources: The Bank for International Settlements.

Figure 1.2: Percentages of Single-Name CDS Contracts Cleared by CCPs



Notes: This figure depicts the ratios of the notional amounts outstanding of single-name CDS contracts traded by CCPs to that traded by all types of counterparties. Data sources: The Bank for International Settlements.

Chapter 2: Dynamics and Determinants of Credit Risk Discovery: Evidence from CDS and Stock Markets

2.1 Introduction

Credit default swap (CDS) is invented to benefit credit risk transfer, provide credit risk discovery, and generate liquidity for credit risk trading (Stulz, 2010). However, due to insider trading problem, potential price manipulation, the opaque over-the-counter (OTC) market structure, and relatively inadequate regulation, the CDS market has been widely criticised (e.g., Acharya and Johnson, 2007; Cecchetti et al., 2009; Marsh and Wagner, 2015). Among the discussions regarding the economics of the CDS market, whether credit risk is priced timely in CDS spread, especially during the recent financial crises, is an important question to academics, policymakers, and practitioners alike. Distinct market structures and different investors may cause the prices of different assets to respond to credit risk news non-synchronously (Norden and Weber, 2009). Accordingly, it is of interest to identify which market reflects credit risk information first and what factors explain its informational dominance, so that market participants can design optimal trading strategies and regulators can monitor information flows across markets (Avino et al., 2013).

With respect to credit risk, three most important markets are stock, bond, and CDS markets. While it is generally agreed that bond market takes a longer time than stock and CDS markets to incorporate credit risk information (e.g., Longstaff et al., 2003; Forte and Peña, 2009), there is no consensus about credit risk discovery leadership between stock and CDS markets (e.g., Norden and Weber, 2009; Acharya and Johnson, 2007; Marsh and Wagner, 2015). In this regard, it is worth of revisiting credit risk discovery mechanism between the two markets. Several research gaps need to be filled.

Firstly, an essential assumption of the widely used Hasbrouck's (1995) information share (IS) and Gonzalo and Granger's (1995) component share (GG) is that all the assets should have the same efficient price in the long run, which is referred to as one-to-one cointegration. However, as discussed by Lien and Shrestha (2014), this assumption may be only applicable to almost identical assets, e.g., cross-listed stocks. For CDS and stock, their credit risk proxies may fail to satisfy the one-to-one relation due to market frictions, e.g., transaction cost, liquidity risk, counterparty risk, and different market structures. Thus, it might be inappropriate to apply IS and GG methods. To address this issue, we use the generalized information share (GIS) developed by Lien and Shrestha (2014). GIS does not require the pair to be one-to-one cointegrated and is more suitable for this study. A comparable analysis is conducted by comparing the results of GIS with that of IS and GG. Second, because credit risk is related to the permanent price component, eliminating transitory effects from asset prices is expected to provide a clearer view on credit risk discovery (Forte and Lovreta, 2015). Thus, this study eliminates transitory components from asset quotes or prices to extract the permanent price component.

In addition, identifying the factors that drive credit risk discovery process is another important topic. Previous papers have discussed the impact of market liquidity, credit quality of the underlying reference entity, adverse credit risk shocks, and firm-specific and macroeconomic news releases on the informational efficiency of CDS and stock markets (e.g., Forte and Lovreta, 2015; Hilscher et al., 2015). Nonetheless, these papers do not well consider the effects of the overall economy condition, funding cost, and the newly introduced central clearing counterparty (CCP) in the CDS market on credit risk discovery between the two markets. Specifically, previous studies use dummy variable or sub-sample analysis to examine the impact of financial crisis on credit risk discovery between CDS and stock (e.g., Xiang et al., 2013). However, both approaches suffer from an arbitrary dating issue. Therefore, we suggest using the financial condition index (FCI). As argued by Kliesen et al. (2012), since FCIs are constructed by using a wide variety of financial and non-financial variables to measure systematic risk not only in the financial market but also in the macro economy, they are capable of quantitatively, continuously, and timely indicating and even predicting the circumstance of the whole economy. Similar to transaction cost, funding cost may impose constraints on investors' trading decisions and affect their capital allocations across assets (Augustin et al., 2014). Hence, funding cost is expected to exert effect on credit risk discovery process. The advent of central clearing counterparty (CCP) results in a hybrid structure in the CDS market and affects its counterparty risk, liquidity, and trading (Loon and Zhong, 2014). This chapter concentrates on assessing the impact of CCP on the relative informational efficiency between CDS and stock markets. Therefore, this chapter aims at providing further evidence on credit risk discovery between CDS and stock by employing more robust methodologies and probing further into the driving forces underlying the credit risk discovery process. In particular, we address the following research questions.

a) Which market, CDS or stock, discovers credit risk information first?
b) What factors affect the credit risk discovery process between CDS and stock?

The major findings are summarised as follows. The empirical results show that in most cases, credit risk proxies of CDS and stock markets are not one-to-one cointegrated, which justifies the use of GIS instead of two conventional price discovery contribution measures, that is, IS and GG. Stock generally dominates CDS in discovering credit risk news, except for the relatively turbulent period of 2008–2010. Eliminating transitory price components increases the informational efficiency of the CDS market in the earlier period of the sample. The CDS of investment-grade firms presents a higher credit risk discovery contribution compared with that of speculative-grade firms. The overall economy condition and funding cost negatively affect the informational efficiency of the CDS market. Finally, contrary to the conventional wisdom that CCP should enhance CDS market efficiency, centrally clearable CDS presents a lower credit risk discovery contribution, suggesting that the CDS market may be driven largely by insider trading.

This chapter adds to the existing literature in the following aspects. First, we contribute to the extant literature related to applying GIS in empirical studies, e.g., Shrestha (2014). By comparing the results of GIS and that of IS and GG, we suggest that although GIS is theoretically stronger than IS and GG, it may not substantially alter empirical results. However, since this chapter considers two assets, further research is needed to confirm whether this finding holds in the case of more than two assets. Second, complementing previous literature, e.g., Forte and Peña (2009) and Narayan et al. (2014), this chapter provides further evidence to support the informational dominance of the stock market. However, over the crisis period of 2008–2010, the CDS market generally dominates the stock market, which supports Xiang et al. (2013). Unlike Forte and Lovreta's (2015) research which concentrates on the European firms, this study provides further evidence of the impact of eliminating transitory components from asset prices on price discovery. For the U.S. non-financial companies, the impact is time-varying, but not substantial on average. This chapter also extends the existing understanding of the determinants of credit risk discovery process of CDS and stock markets by suggesting several new factors. In particular, the adverse effect of CCP on the informational efficiency of the CDS market provides important implication to the regulators to improve their policy.

The rest of this chapter is organised as follows. Section 2.2 reviews related literature and develops hypotheses. In Section 2.3, an improved procedure to measure credit risk discovery is described. This includes elimination of the transitory components from the price, calculation of the credit spread implied by the stock price, and calculation of GIS, IS, and GG measures. This section also describes the regression we use to examine the newly proposed drivers of credit risk discovery. Section 2.4 presents the data and preliminary data analysis. Section 2.5 is devoted to empirical analyses using individual firm data from the United States. Section 2.6 is the conclusion.

2.2 Related Literature and Hypothesis Development

2.2.1 Price Discovery Hypotheses

Price discovery hypotheses proposed by prior literature provide intuitive interpretations about why one market can impound new information more rapidly than the others. This section reviews the hypotheses related to credit risk discovery. First, the liquidity hypothesis implies that informed trading is more likely to be operated in more liquid markets since traders can exploit the profits of their informational advantages without causing large market price movements (Garbade and Silber, 1983). Second, the trading cost hypothesis states that new information would be incorporated firstly in the lowest-cost market because investors prefer to execute their information-based trades where maximum net profits can be exploited (Fleming et al., 1996). Third, the market trading mechanism hypothesis shows that compared with floor trading mechanism, electric trading platform can promote one market to reflect new information (Martens, 1998).

Fourth, the news-specific hypothesis implies that prices of several securities may be more sensitive to market-wide news, while prices of others may adjust more quickly in response to firm-specific news (Chan, 1992). A similar hypothesis is the insider trading hypothesis proposed by Acharya and Johnson (2007), who find that informed traders are in favour of trading in one market for at least three reasons. Trading on private information may not be detected easily and penalised severely. Also, direct hedging can be done without unnecessary portfolio rebalancing. Moreover, there are limited market constraints, such as short-sale restrictions. Finally, the market maturation hypothesis suggests that the degree of market maturation can also affect the price discovery ability of a market since market participants may prefer to trade securities with well-developed markets (Chiang and Fong, 2001).

Based on the implications of the above reviewed price discovery hypotheses, Table 2.1 summarises the expectations on the dominant role of credit risk discovery between stock and CDS markets. On the one hand, the stock market has lower transaction costs, relatively higher liquidity, a longer history, and a more transparent and mature trading mechanism. On the other hand, the CDS market has an opaque OTC market structure, provides investors an option to transfer credit risk directly, and possesses large financial institutions as major participants. Also, since the recent financial crises, regulators have implemented several initiatives which bring the CDS market into a new epoch, such as the central clearing services in 2009. However, it is important to acknowledge that the possible driving forces are not mutually exclusive and they may jointly determine one market's dominant role in incorporating news (e.g., Ates and Wang, 2005).

2.2.2 Price Discovery Contribution Measures

According to So and Tse (2004), there are three approaches to study price discovery: lead-lag relations, volatility spillovers, and price discovery contributions (Table 2.2).[2] For lead-lag relations, the general idea is that if the lagged returns of market A can predict the current returns of market B, then market A leads market B in price discovery. Nevertheless, Hasbrouck (1995) points out that lead-lag relations provide only general

[2] A more detailed review of econometric tools of price discovery contributions can be found in Putniņš (2013) and Narayan and Smyth (2015). Also, according to the seminal papers of French and Roll (1986) and Ross (1989), in an arbitrage-free framework, variance of asset returns can be a proxy for variance of information flows. Hence, volatility transmission patterns among relevant markets can indicate which market is the source of information flows. Since volatility spillover is beyond of the scope of this study, we do not review this method in detailed in this section.

views of informational dominance, are applicable only for short-run analysis, and rely on the assumption that convergence relations exist, such as futures and spot markets. Therefore, to quantify informational efficiency of interrelated markets and exploit long-term equilibrium relations shared by prices, Hasbrouck (1995) proposes information share (IS) and Gonzalo and Granger (1995) suggest component share (GG).

Hasbrouck (1995) assumes that the observed prices of one security in multiple markets comprise two components: a common implicit efficient price for all the markets and innovations which are attributable to individual markets. He defines a market's IS as its relative contribution to the total variance of the innovations in the common permanent component. A market with a higher IS implies that it has higher informational intensity of the equilibrium price than the other markets and it dominants price discovery process. However, due to the ordering problem of Cholesky factorisation, Hasbrouck's (1995) IS measure is not unique. This issue is addressed by Lien and Shrestha (2009) and Grammig and Peter (2013). Also, Lien and Shrestha's (2014) GIS relaxes the one-to-one cointegration relation assumed by Hasbrouck (1995). Hasbrouck (2003) suggests using high frequency data to eliminate contemporaneous correlations of the innovations and to obtain a more accurate IS measure. However, for several assets, such as single-name CDS, intraday data may not be available (Chen et al., 2011). Grammig and Peter (2013) alleviate this drawback by exploiting the tail dependence of return distributions. However, their method has the prerequisite of tail dependence and may not be robust to all the assets (Lien and Wang, 2016).

Gonzalo and Granger's (1995) permanent-transitory (P-T) decomposition focuses only on the error correction process. Booth et al. (1999) and Harris et al. (2002) define price discovery as the process by which markets incorporate information to reach equilibrium asset prices and apply the P-T method to calculate component share (GG). One market with a higher GG suggests that it contributes a higher proportion to the innovations in the common stochastic trend than the other markets; therefore, it leads price discovery. However, the GG measure also imposes the one-to-one cointegration restriction. By extending Garbade and Silber's (1983) model, Figuerola-Ferretti and Gonzalo (2010) elaborate the use of the P-T method to calculate the GG measure when the cointegration vector is unrestricted to be one-to-one.

In Figucrola-Ferrctti et al.'s (2014) paper, they explain the differences among IS, GG, and GIS. IS offers the greatest weight to the market incorporating the most information, whereas the market with the greatest IS cannot necessarily provide the best benchmark for the implicit efficient price. GG quantifies the extent to which different market prices reflect the long-run equilibrium price. Hence, the dominant market identified by GG can offer the best benchmark for the fundamental price. GIS imposes a different factor structure on the innovations, and it is a rotation of principal component analysis (PCA) factors which define the weights of PCA factors as the fractions that they contribute to each market price. The price of the market with the greatest GIS can be interpreted as a weighted average of all market prices, approximating the efficient price. IS, GG, and GIS also share several similarities. For example, for each measure, the price discovery contributions of all the examined markets sum to 1 (Lien and Shrestha, 2014). Therefore, in the case of two markets, the higher values of these measures of one market indicate that this market (the other market) contributes relatively more (less) to price discovery.

2.2.3 Previous Empirical Findings of Credit Risk Discovery

The prior empirical evidence presents complex credit risk discovery patterns between CDS and stock markets. For example, using panel VAR and firm-specific VAR models, Norden and Weber (2009) suggest that stock dominates CDS in most cases, which is supported by Forte and Peña (2009), who employ IS and GG measures. Unlike these two studies which examine international samples, Narayan et al. (2014) and Hilscher et al. (2015) focus on the U.S. firms. Hilscher et al. (2015) rely on a panel VAR framework, while Narayan et al. (2014) calculate IS and GG measures in a panel VECM model that permits the heterogeneity in CDS spreads caused by sector, credit rating, and firm size. Both papers confirm that stock generally leads CDS. However, by testing whether CDS innovations permanently affect stock prices during the period 2001–2004, Acharya and Johnson (2007) document that the U.S. CDS market tends to incorporate negative credit risk news first because of its more severe insider trading problem. The dominant role of the CDS of the U.S. investment-grade firms from 2005 to 2009 is detected by Xiang et al. (2013), who use IS and GG measures. Moreover, Longstaff et al. (2003) find that CDS and stock markets present similar speeds to incorporate credit risk news, which is supported by Marsh and Wagner (2015), who document that the similar information processing speeds emerge when negative firm-specific news arrives. Both papers use VAR model and concentrate on the U.S. financial market. Using the rolling-window method and IS and GG measures, Forte and Lovreta (2015) investigate the time-varying credit risk discovery relation between the two assets in Europe from 2002 to 2008. They conclude that stock dominates credit risk discovery in the financial crisis, while CDS impounds credit risk news more rapidly during the tranquil times.

Table 2.3 briefly summarises the previous findings related to the driving forces of credit risk discovery process between CDS and stock. Forte and Lovreta (2015) confirm that market liquidity is positively associated with one market’s informational efficiency. Norden and Weber (2009) and Forte and Lovreta (2015) show that the lower credit quality of the reference entity is, the greater information flows from stock to CDS, while Acharya and Johnson (2007) find the opposite. Credit downgrades and adverse credit risk shocks are generally discovered first by the CDS market (Norden and Weber, 2004; Wang and Bhar, 2014). Moreover, Hilscher et al. (2015) suggest that higher transaction costs hinder the CDS market from impounding news rapidly. Both macroeconomic and earnings announcements can also affect the lead-lag relations between CDS and stock markets (Hilscher et al., 2015; Marsh and Wagner, 2015).

To extend the existing understanding of the possible driving forces of the informational efficiency of CDS and stock markets, this chapter proposes three factors, i.e., financial condition index, funding cost, and central clearing service. Firstly, when the economy is under stress, increased default risk may increase hedgers' demand for CDS contracts, and the high and volatile CDS spreads may also attract arbitragers and speculators with inside information (Xiang et al., 2013). As argued by Garbade and Silber's (1983), one market's price discovery ability is positively related to the number of its market participants. Hence, during the turmoil times, more information is expected to flow into the CDS market, and it would be the primary market of credit risk discovery. However, previous empirical studies have disagreements with regard to the direction of the impact of financial crisis on credit risk discovery. Xiang et al. (2013) find that the dominant role of CDS is enhanced during the sub-prime crisis. On the contrary, Forte and Lovreta (2015) find that stock contributes more to credit risk discovery over the dot-com bubble and the sub-prime crisis. Narayan et al. (2014) claim that financial crisis can induce a lagged market to be a credit risk discovery leader. Based on the above argument of the possible negative relation between the macroeconomic and financial environment and the number of market participants in the CDS market, the following hypothesis is tested.

Hypothesis 1: When the overall economy is stressful, the CDS market presents a higher credit risk discovery contribution.

The second factor that is likely to affect the dynamics of credit risk discovery is funding cost. Similar to transaction costs, investors' investment decisions could be affected by their funding cost (Augustin et al., 2014). As suggested by the trading cost hypothesis, price discovery would be produced by the lowest-cost market because investors would like to exploit their informational advantages in the market where they obtain maximum net profits (Fleming et al., 1996). Also, Brunnermeier and Pedersen (2009) emphasise the importance of funding constraints and argue that '*when funding liquidity is tight, traders become reluctant to take on positions, especially "capital intensive" positions in high-margin securities*'. According to the margin requirements for CDS transactions set by the Financial Industry Regulatory Authority (FINRA), shorting a 5-year single-name CDS contract requires a margin of 4% to 25% of the notional amount. In addition, the margin requirement for speculative-grade CDS can be three to six times higher than that for investment-grade CDS (Kapadia and Pu, 2012). Hence, when the funding cost is high and volatile, traders would prefer the stock market to the CDS market. Consequently, it is anticipated that a rise in funding cost would result in an increased contribution of the stock market to credit risk discovery.

Hypothesis 2: The higher funding cost is, the lower contribution the CDS market makes to credit risk discovery process.

The third factor is the newly introduced central clearing counterparty in the CDS market. In December 2009, ICE Clear Credit, the first CDS clearing house launched by the Intercontinental Exchange (ICE), started to provide a single-name CDS central clearing service for the U.S. market.[3] Distinct views about the question of whether the central

[3] There are two approved CCPs in the U.S., the ICE Clear Credit (previously called the ICE Trust) and the CME Group. The clearable instruments of the ICE Clear Credit include both single-name corporate CDS contracts and CDS indices, whereas the CME Group is only involved in clearing CDS indices.

clearing counterparty (CCP) can effectively promote CDS market efficiency exist. On the one hand, Duffie and Zhu (2011) argue that introducing CCP only in the CDS market rather than in all the relevant OTC markets and constructing multiple CCPs instead of a unique CCP would reduce bilateral netting benefits and raise counterparty risk, unless the clearable exposures in the CDS market are sufficiently larger than the bilaterally netted exposures. Supporting Duffie and Zhu's (2011) theoretical analysis, Arora et al. (2012) empirically prove that the current risk mitigation arrangements in the CDS market, e.g., the overcollateralization of CDS liabilities and the use of ISDA master agreements, can successfully manage a dealer's credit risk. Thus, CCP may not help reduce counterparty risk further. On the other hand, Acharya and Bisin (2014) theoretically present that by disclosing trade positions of participants, CCP can lower counterparty risk in CDS trades. Loon and Zhong (2014) empirically confirm that CCP can reduce counterparty risk and systemic risk and improve single-name CDS's post-trade transparency. Similar results are found by Mayordomo and Posch (2016) in the CDS index market. The market trading mechanism hypothesis implies that an improved trading mechanism facilitates one market to discover new information (Martens, 1998). In general, CCP is expected to enhance the CDS market transparency and accelerate contract settlement. Accordingly, this chapter tests the following hypothesis.

Hypothesis 3: For a firm for which CDS contract is clearable through CCP, the credit risk discovery contribution of its CDS market increases.

2.3 Methodology

Since this chapter focuses only on single-name corporate CDS contracts, all the clearable CDS contracts considered in this study are cleared by the ICE Clear Credit.

This section first briefly outlines an improved procedure to calculate each market's contribution to credit risk discovery. The procedure consists of three steps: a) extracting permanent price component from stock prices and CDS spreads, b) calculating implied credit spreads from stock prices, and c) calculating credit risk discovery contribution of each market. Then, the panel regression used to test determinants is discussed.

2.3.1 Permanent Price Component

The observed price is driven by many factors, such as permanent change in firm value and transitory change in liquidity. As our focus is on the credit risk component of the price, which is based on the long-term value of a firm, using the price as it is could be misleading because it may obscure the pure credit risk component and the credit risk discovery relation obtained from it. Eliminating any transitory effects from the price is expected to provide a clearer view about credit risk discovery.[4] In fact, this is briefly discussed by Forte and Lovreta (2015), who eliminate transitory liquidity components in their robustness test. They report that removing the transitory components does not significantly affect the credit risk informational dominance between stock and CDS markets in Europe. This chapter brings this forward and focuses on the U.S. firms. All the empirical analyses are conducted by using two sets of data: original prices and permanent price component time series.

Similar to Forte and Lovreta (2015), this chapter employs Gonzalo and Granger's (1995) P-T decomposition method to eliminate transitory components from stock prices and CDS quotes. First, specify a bivariate vector error-correction model (VECM) of bid and ask prices/quotes for each market.

[4] Putniņš (2013) also argues that prices usually have unequal levels of noise, such as microstructure frictions and liquidity; therefore, IS and GG may provide misleading conclusions about price discovery leadership as they measure a combination of price discovery leadership and relative avoidance of noise.

$$\Delta B_t = c_1 + \alpha_1 EC_t + \sum_{i=1}^{k} b_{1i} \Delta B_{t-i} + \sum_{i=1}^{k} d_{1i} \Delta A_{t-i} + \epsilon_{1t} \tag{2.1}$$

$$\Delta A_t = c_2 + \alpha_2 EC_t + \sum_{i=1}^{k} b_{2i} \Delta B_{t-i} + \sum_{i=1}^{k} d_{2i} \Delta A_{t-i} + \epsilon_{2t} \tag{2.2}$$

where B_t and A_t are respectively bid and ask prices/quotes at time t and $EC_t = B_{t-1} + \gamma_0 - \gamma_1 A_{t-1}$ is the error correction process. Lag k is determined based on Schwarz Information Criterion (SBC). Then, the permanent price component (LP) is given by:

$$LP_t = \frac{\alpha_2}{\alpha_2 - \alpha_1} B_t + \frac{\alpha_1}{\alpha_1 - \alpha_2} A_t \tag{2.3}$$

This estimation procedure is repeated for both stock prices and CDS quotes.

2.3.2 Implied Credit Spread

Forte and Peña (2009) argue that stock price is not comparable with CDS spread as credit spread is determined by many variables, such as firm asset value, asset volatility, leverage, and risk-free rate. Hence, they advocate using credit spread implied in stock price which considers the variations in not only stock price, but also liabilities, risk-free rate, and other factors related to firms' default risk. The use of implied credit spread is also supported by Avino et al. (2013) and Xiang et al. (2013), among others. This study follows these prior studies to adopt Finger et al.'s (2002) CreditGrades model to derive the stock implied credit spread (ICS). Unlike other structural pricing models, the CreditGrades model does not suffer from an under-pricing problem and thus has been widely used in the literature to extract implied credit risk information (e.g., Byström, 2006; Yu, 2006). However, apart from stock price, stock volatility, debt per share, and risk-free rate, other key parameters in the CreditGrades model, such as the asset-specific recovery rate, R, and the mean and standard deviation of the average recovery rate, L, are not directly observable. Following Avino et al. (2013), this study uses the Moody's average historical recovery rate on senior unsecured debt as a proxy for R and sets $R =$

0.374.[5] Given the absence of industry guidelines for setting the mean ($\bar{L}$) and standard deviation (λ) of the average recovery rate, L, both $\bar{L}$ and λ for the firm i are calibrated to minimise the sum of squared difference between CDS spread (CS) and ICS using the first 20 daily observations, and the calibrated values are used for the whole sample.[6]

$$[\bar{L}_i^*, \lambda_i^*] = argmin \sum_{j=1}^{20} \left(ICS_{i,t-j}(\bar{L}_i, \lambda_i) - CS_{i,t-j}\right)^2 \quad (2.4)$$

Details of the CreditGrades model and ICS calculation are reported in Appendix 2A.

2.3.3 Generalized Information Share

After obtaining the time series of CS and ICS, the credit risk discovery contribution of each market can be calculated. The most commonly used measures are Hasbrouck's (1995) IS and Gonzalo and Granger's (1995) GG. Both IS and GG are established under the assumption that the common factor shared by interrelated markets have the same long-run equilibrium price, i.e., a one-to-one cointegration. However, this assumption is realistic only for almost identical assets, such as cross-listed stocks. In fact, as shown in Section 2.4.3, CS and ICS do not satisfy the one-to-one cointegration requirement. This motivates this chapter to employ an alternative measure that has been recently developed by Lien and Shrestha (2014), which is unique and does not assume one-to-one cointegration. It only requires that all the $I(1)$ time series share one and only one common stochastic trend. This study uses this generalised information share (GIS) as the main toolkit for credit risk discovery analysis and compares it with IS and GG

[5] The Moody's average historical recovery rate on senior unsecured debt is reported by Ou et al. (2011).

[6] In the existing literature that uses the CreditGrades model, there are disagreements related to whether and how to calibrate $\bar{L}$ and λ. For instance, Yu (2006) assumes $\lambda = 0.3$ and calibrates $\bar{L}$, while Byström (2006) calibrates both $\bar{L}$ and λ. Both of them calibrate the parameters to minimise the sum of squared difference between CS and ICS using the first 10 daily data and then use the calibrated parameters for the whole sample. Xiang et al. (2013) re-calibrate both $\bar{L}$ and λ every 30 days. Avino et al. (2013) do not conduct calibration and assume $\bar{L} = 0.5$ and $\lambda = 0.3$ reported by Finger et al.'s (2002) for all firms.

throughout the empirical analyses. The reminder of this section briefly describes the calculations of IS, GG, and GIS measures.

First, specify the VECM model of CS and ICS as follows:

$$\Delta CS_t = c_1 + \alpha_1 EC_t + \sum_{i=1}^{k} b_{1i} \Delta CS_{t-i} + \sum_{i=1}^{k} d_{1i} \Delta ICS_{t-i} + \epsilon_{1t} \tag{2.5}$$

$$\Delta ICS_t = c_2 + \alpha_2 EC_t + \sum_{i=1}^{k} b_{2i} \Delta CS_{t-i} + \sum_{i=1}^{k} d_{2i} \Delta ICS_{t-i} + \epsilon_{2t} \tag{2.6}$$

where $EC_t = CS_{t-1} + \lambda_c - \lambda_1 ICS_{t-1}$. $\lambda = [1, -\lambda_1]'$ implies the long-run equilibrium relationship between CS and ICS. Let $\alpha = [\alpha_1, \alpha_2]'$, with α_1 and α_2 denoting short-run adjustment speeds. Let $\epsilon_t = [\epsilon_{1t}, \ \epsilon_{2t}]'$ and $E[\epsilon_t \epsilon_t'] = \Omega$. Equation (2.5) and (2.6) can be rewritten in the vector moving average form:

$$CS_t = CS_0 + \psi_1(1) \sum_{i=1}^{t} \epsilon_{1i} + \psi_1^*(L) \epsilon_{1t} \tag{2.7}$$

$$ICS_t = ICS_0 + \psi_2(1) \sum_{i=1}^{t} \epsilon_{2i} + \psi_2^*(L) \epsilon_{2t} \tag{2.8}$$

where $\psi_i(1), i = 1, 2$, are the sum of the moving average coefficients. Let $\Psi(1) = [\psi_1(1), \ \psi_2(1)]'$. The Engle-Granger representation theorem implies that $\lambda' \Psi(1) = 0$ and $\Psi(1)\alpha = 0$. Under the assumption that $\lambda = [1, -1]'$, $\Psi(1)$ has identical rows. Let ψ be the identical row of $\Psi(1)$. Hasbrouck's (1995) IS and Gonzalo and Granger's (1995) GG are defined as:

$$IS_j = \frac{[\psi F]_j^2}{\psi \Omega \psi'}, \ GG_j = \left[\frac{\alpha_2}{\alpha_2 - \alpha_1}, \frac{\alpha_1}{\alpha_1 - \alpha_2}\right]' \tag{2.9}$$

where F is the Cholesky factorisation of Ω and j = 1, 2. Baillie et al.'s (2002) approach is adopted and a unique IS is approximated as the midpoint of the upper and lower bounds. Also, as suggested by Forte and Lovreta (2015), the GG values that exceed the range [0, 1] are replaced with the boundary values.

For GIS, the factor structure of ϵ_t focuses on the diagonalization of the correlation matrix rather than the covariance matrix Ω. Denote Φ as the correlation matrix of the residuals and Λ as a diagonal matrix which has the eigenvalues of Φ on the diagonal. The corresponding eigenvectors construct a matrix G. Let W be a diagonal matrix having the standard deviations of the residuals on the diagonal. The cointegrating vector is unrestricted, so that λ_1 is not necessary to be 1. Let ψ_j^λ be the j-th row of $\Psi(1)$. According to the Engle-Granger representation theorem, $\psi_1^\lambda = \lambda_{j-1}\psi_j^\lambda, j = 1, 2$, with $\lambda_0 = 1$. Then, GIS can be computed as:

$$GIS_j = \frac{\left(\psi_j^G\right)^2}{\psi_1^\lambda \Omega (\psi_1^\lambda)'} \tag{2.10}$$

where $\psi^G = \psi_1^\lambda F^M$, $F^M = [G\Lambda^{-0.5}G'W^{-1}]^{-1}$, $\epsilon_t = F^M z_t$, $E[z_t] = 0$, $E[z_t z_t'] = I_2$.

The values of IS, GG, and GIS generally range from 0 to 1. The higher values of these measures indicate the higher contributions of related asset prices to price discovery. To obtain the dynamics of credit risk discovery contribution, we follow Forte and Lovreta (2015) to update these indicators daily using a 120-day rolling window.

2.3.4 Determinants of Credit Risk Discovery

We construct a panel regression equation using the three factors proposed above, that is, financial condition index (FCI), funding cost (FC), and central clearing counterparty (CCP). Among the existing financial condition indices, Bloomberg Financial Condition Index (BFCIUS) and Goldman Sachs Financial Condition Index (GSFCI) are used due to their daily frequency.[7] Following Acharya et al. (2015), we use the spread between

[7] BFCIUS is an equally weighted sum of three major sub-indices: money market indices, bond market indices and equity market indices. GSFCI is set to be 100 on the benchmark day, 20/10/2003. It is different from other FCIs as it is constructed by using levels of financial indicators rather than spreads

the 3-month financial commercial paper interest rate and 3-month T-bill rate as a proxy for the overall funding cost. Moreover, using a dummy variable for CCP-clearable CDS (which equals one from the first clearing date to the end of the sample period for the clearable CDS and zero otherwise), this study examines whether CCP can benefit the CDS market in detecting credit risk news.

This chapter includes the four factors found significant in Forte and Lovreta (2015) as control variables. They are the relative market liquidity between CDS and stock markets (RML), the credit condition of reference entity (CCON), the relative frequency of adverse shocks (ADS3), and credit rating downgrade events (CRDOWN). The bid-ask spreads relative to the mid-quote price for the stock market and the CDS market are computed, respectively, and they are averaged over the past 120 days. RML is defined as the ratio of the average stock bid-ask spread to the average CDS bid-ask spread. CCON is defined as the time-varying mean of each firm's CDS spread, calculated from the 120-day rolling window. ADS3 is defined by the following equation:

$$ADS3 = \frac{No.\ of\ ((x_t - \bar{x}) > 3 * \sigma)}{120} \tag{2.11}$$

where x_t is CDS spread at time t, and $\bar{x}$ and σ are sample mean and standard deviation of the CDS spread obtained from the sample $[x_{t-120}, \dots, x_{t-1}]$. CRDOWN takes value of 1 if a credit rating downgrade occurs during the past 120 days and 0 otherwise. The final panel regression equation has the following form:

$$y_{it} = \beta_0 + \beta_1 FCI_t + \beta_2 FC_t + \beta_3 CCP_{it} + \beta_4 RML_{it} + \beta_5 CCON_{it} + \beta_6 ADS3_{it} + \beta_7 CRDOWN_{it} + e_{it} \tag{2.12}$$

or changes in those variables (Kliesen et al., 2012). To ensure that GSFCI and BFCIUS are comparable, we adjust GSFCI by subtracting 100 from its original values.

where y_{it} is a price discovery contribution measure (GIS, IS, or GG) of CDS of firm i at time t. Because the GIS (IS or GG) of CDS and that of stock of one firm sum to 1, this regression can also provide us indirect evidence about the impact of these factors on the price discovery contribution of stock.

2.4 Data

2.4.1 Data Sources

The sample consists of liquid U.S. dollar-denominated 5-year CDS contracts written on senior unsecured debts from January 1, 2006 to December 31, 2013. Since the focus is on the corporate level, CDS contracts on sovereigns are excluded. CDS contracts on financial firms are also excluded due to their distinguished capital structures. Given the changes in contract and convention since the 2009 CDS 'Big Bang', No Restructuring (XR) clauses are preferred. Finally, this chapter considers only active CDS contracts by dropping the firms whose CDS data are consecutively unavailable for more than 90 business days within one year.[8] Daily CDS data are collected from two data sources: CMA in DataStream (before September 30, 2010) and Markit in TickHistory (from September 30, 2010).[9] Financial data of the stock market, such as stock prices, market capitalizations, and liabilities, are obtained from Bloomberg. After filtering, the sample comprises 113 non-financial firms from nine industry sectors. In addition, this chapter

[8] Avino et al. (2013) follow Longstaff et al. (2003) to select the companies that at least 100 observations per year are simultaneously available for CDS, bond, stock, and option. For the same purpose, Forte and Lovreta (2015) remove the firms with no trades or trades available for less than 5% of trading days in any of the corresponding years. Compared to their methods, the filtering criterion of this chapter seems to be more rigorous. However, it can retain the firms with sufficient daily observations of CDS and stock, which may benefit the following cointegration analysis.
[9] Due to a contract issue, CMA CDS data are available in DataStream only until September 30, 2010. In TickHistory, the majority of Markit CDS data are available after November 1, 2010. Mayordomo, Peña, and Schwartz (2013) compare five CDS databases—GFI, Fenics, Reuters EOD, CMA, and Markit—and find that CMA and Markit are more consistent with each other. Loon and Zhong (2014) also show that between 2009 and 2011, differences between CDS spreads provided by CMA and Markit are negligible for the U.S. single-name CDS market. Hence, it is expected that the merge of two databases may not influence the results significantly.

follows Blanco et al. (2005) and Forte and Peña (2009) to employ a 5-year swap rate as a default-free interest rate. Table 2.4 summarises all the data required for the empirical analysis and their sources.

2.4.2 Preliminary Data Analysis

Figure 2.1 displays the distributions of the firms in the sample across credit ratings and industry sectors. Credit ratings are based on the S&P Domestic Long Term Issuer Credit Ratings as of 31/12/2013. Among 113 firms, 94 firms (83%) are investment-grade firms (BBB or higher) and 19 firms (17%) are speculative-grade firms (BB or lower). The firms spread across industries with no highly concentrated industry. The largest sector is Consumer Discretionary, with 28 firms (25%). Throughout this chapter, CS refers to CDS spread, and ICS refers to the credit spread implied by the stock price. LCS and LICS respectively refer to the permanent component of CS and ICS after eliminating transitory components.

Second, we plot the cross-sectional means of CS and ICS in Figure 2.2, and report the summary statistics of CS and ICS time series in Table 2.5 and 2.6. The figure shows that CS and ICS share similar development patterns except for the relatively turbulent period 2009–2010. While CS returns to its previous level quickly, ICS remains high for an extended period. This results in ICS being about 40 basis points (bps) higher than CS: 172.23 bps (LICS) versus 128.09 bps (LCS) and 168.69 bps (ICS) versus 127.24 bps (CS), which can be seen in Table 2.5. Although short-term discrepancies exist between each pair of credit spreads during some periods, the generally comparable dynamics imply the existence of cointegration in most pairs. Comparing the two graphs in Figure 2.2, it appears that eliminating transitory components from the prices does not make substantial differences. As shown in Table 2.5, the overall credit spreads increase slightly after eliminating transitory components: 0.85 bps for CS and 3.54 bps for ICS. Nevertheless, the difference is more distinguishable at the individual firm level (not reported here). In general, when the credit spread level is high, its standard deviation is high as well. This is also true across credit ratings, as shown in Table 2.6. Except for the reversal between B and CCC, a higher rating is associated with a lower credit spread and a lower credit spread variation.

Third, using the Augmented Dickey-Fuller (ADF) unit root test, this chapter examines whether CS and ICS follow $I(1)$ process. We also test the one-to-one cointegration between CS and ICS by testing the stationarity of their difference: if CS and ICS are one-to-one cointegrated, the difference should be stationary (Lien and Shrestha, 2014). Table 2.7 summarises the results and the full test statistics are in Appendix 2B. The test statistics show that CS (LCS) and ICS (LICS) are $I(1)$ series and they do not satisfy the one-to-one cointegration assumption in most cases. This justifies the choice of GIS over IS or GG measures. After testing unit root, we proceed to find the cointegration relations using Johansen cointegration test. The number of lags is determined by SBC. As shown in Table 2.8, cointegration is detected in 60% of the firms in LCS-LICS pairs and 71% of the firms in CS-ICS pairs. Forte and Lovreta (2015) argue that the power of cointegration test may depend on the length of sample period and a failure to statistically detect cointegration may not necessarily imply the non-existence of long-run equilibrium relation. Hence, to avoid omitting any possible cointegration relations, we follow them to retain all the firms in the sample regardless of the test results. In Section 2.5.3, the sensitivity of the results is tested by repeating the estimations for a sub-sample of firms for which the cointegration relations statistically exist.

Finally, Figure 2.3 and 2.4 depict the U.S. financial condition index and the overall funding cost, respectively. Figure 2.3 shows that a lower (higher) BFCIUS (GSFCI) indicates a higher level of stress in the U.S. economy. The sample average of BFCIUS (GSFCI) is -0.82 (-0.05) with a standard deviation of 2.07 (1.06). As seen from Figure 2.4, the overall funding cost increases substantially from just above 0.2% in 2006 to roughly 3.7% in 2008. After 2008, accompanied with a series of monetary policies implemented by the U.S. government to curb the global financial crisis, the financing cost declines in 2009 and then remains to be less than 0.5% until the end of our sample period. Table 2.9 reports the first clearing dates of each clearable CDS contract. For 56 of 113 non-financial reference entities, their CDS contracts are clearable.[10] There are 22 separate clearing dates over the period of 2010–2013. The number of CDS contracts cleared on each date ranges from one (e.g., June 15, 2011) to six (February 19, 2010).

2.5 Empirical Results

2.5.1 Contributions of Credit Risk Discovery

The contribution of each market to credit risk discovery is quantified by three measures: GIS, IS, and GG. These indicators are updated daily using a 120-day rolling window. The cross-sectional averages of GIS, IS, and GG of CDS are plotted in Figure 2.5. More detailed views of these metrics are also reported in Table 2.10 and 2.11. Table 2.10 is for the results from LCS and LICS and Table 2.11 is for the results from CS and ICS. As the two sets of results are similar, the following analysis is based on the results of LCS and LICS.

It appears that all three measures offer qualitatively similar patterns. This is consistent with the findings of Lien and Shrestha (2014) and Xiang et al. (2013). However, it is noteworthy that the level of GIS is generally higher than that of the other two measures.

[10] The cleared CDS contracts in the sample are voluntarily cleared by ICE Clear Credit. For the clearable CDS, market participants have two options: either voluntarily clear their trades through the ICE Clear Credit or rely on the extant bilateral counterparty risk reduction arrangements.

For instance, the average GIS over the whole sample period is 0.45, whereas the average IS is 0.37 and the average GG is 0.33. These values by themselves do not suggest which measure should be favoured over the others. Nevertheless, if we consider the fact that current markets are relatively efficient, the GIS measure, which is closer to 0.5, seems to be more reasonable. During the entire sample period, the number of firms for which the average credit risk discovery contribution of CDS is larger than 0.5 is 31% based on GIS. This value is only 8% based on IS and 7% based on GG, which seems to be unrealistic. Also, GIS has a lower volatility over time and less extreme values. All these observations, at least partially, support using GIS for credit risk discovery analysis.

Based on GIS results, the contribution of the CDS market to credit risk discovery is generally smaller than the stock market. This supports prior literature which finds the informational dominance of the stock market, e.g., Forte and Peña (2009) and Hilscher et al. (2015). It contributes to the ongoing debate of the credit risk discovery leadership between CDS and stock by using the advanced price discovery measure. However, over the crisis (February 2008–January 2010), the relative contribution of the CDS market raises and it often exceeds that of the stock market, which is robust to both types of credit spreads. Xiang et al. (2013) also find that the CDS market contributes more to discovery credit risk news in the financial crisis. Table 2.10 reveals another point. While the variation of the number of firms for which CDS is the credit discovery leader (GIS of CS > 0.5) is large, GIS is relatively stable over time. This is the same for IS and GG. It may suggest that even when the credit risk discovery leadership is handed over from one market to the other, the relative informational dominance does not change much.

On average, eliminating transitory price components does not substantially alter the results, which is in line with the findings of Forte and Lovreta (2015). However, if we observe the change at individual firm level, the impact is rather striking. Figure 2.6

highlights the change of credit risk discovery leadership after eliminating transitory components. Overall, there are more firms for which the credit risk discovery leadership is handed over from stock to CDS. This is more apparent in the earlier period of the sample, especially before the sub-prime crisis. This may suggest that the role of CDS market in credit risk discovery was more important than normally believed when it was loosely regulated.

To investigate whether credit ratings have an effect on credit risk discovery contribution, we divide the firms into two groups, that is, investment-grade firms and speculative-grade firms. The GIS for each group is computed. The results are reported in Table 2.12 and the cross-sectional average of GIS for each group is plotted in Figure 2.7. The table shows that the credit risk discovery contribution of CDS is higher for investment-grade firms, which is consistent with Narayan et al.'s (2014) finding. As shown in the figure, it is also less volatile over the sample period. This might result from higher liquidity of the CDS contracts of these firms. However, given the relatively small number of firms with a speculative-grade, more evidence is needed to draw a conclusion.

We also compare the firms whose CDS are centrally clearable with the rest of the firms whose CDS are non-clearable. This can provide some information about the impact of CCP on the CDS market efficiency. The results are presented in Table 2.13. Since the first CCP was introduced in late 2009, the sample period starts from 2010. Although the difference between two groups is generally large in each period, no discernible pattern is observed. In fact, the overall credit risk discovery contribution of the CCP-clearable CDS is smaller than that of non-clearable CDS. This result casts a doubt on the effectiveness of CCP and contradicts the positive effects of CCP documented by Loon and Zhong (2014). To formally and statistically examine the impact of CCP on CDS market efficiency, this chapter also uses panel regression analysis.

2.5.2 Determinants of Credit Risk Discovery

As suggested by Hausman test, we estimate the panel regressions using the fixed-effects model and use robust errors to control for heteroskedasticity.[11] The estimation results for LCS and CS are reported in Table 2.14 and 2.15, respectively. Since the results in the two tables are similar, the following discussions are based on the results for LCS. BFCIUS (GSFCI), the financial condition index which is positively (negatively) related to the U.S. economy condition, has a significant and negative (positive) coefficient, which supports Hypothesis 1. This suggests that the CDS market relatively contributes more to credit risk discovery when the whole economy is under considerable stress. It is consistent with our previous results of the increased credit risk discovery contribution of the CDS market during the period 2008–2010. Over the crisis time, increased number of corporation defaults may increase hedgers' demand for CDS contracts, and the high and volatile CDS spreads may benefit arbitragers and speculators from exploiting their informational advantages from the CDS market. Increased number of traders may be one of the reasons underlying the dominant role of the CDS market when the economy condition is worse. Xiang et al. (2013) draw a similar conclusion in the U.S. market, but Forte and Lovreta (2015) find the opposite in European markets. The funding cost has a significantly negative relation with the credit risk discovery contribution of CDS. This result confirms Hypothesis 2 that a higher funding cost would prevent investors from entering the CDS market, resulting in slower information flows into the market.

The coefficient of CCP dummy is significant and negative. This is contrary to the common belief described by Hypothesis 3 that CCP may enhance the informational

[11] As suggested by Wooldridge (2016, pp.437), since the macro variables (BFCIUS and FC) do not vary across firms on each time point, we consider only firm fixed effects in the regression estimations and do not include time fixed effects.

efficiency and transparency of the CDS market. However, this result has already been anticipated in the previous section, where CCP-clearable CDS is found to have lower credit risk discovery contribution. One possible explanation for this is given by Acharya and Johnson (2007) and Marsh and Wagner (2015). They suggest that a higher level of information asymmetry may motivate insiders to trade CDS rather than stock. However, a more transparent CDS market and a possible rise of collateral requirement related to the centrally clearable CDS contracts may reduce insiders' profits and prompt them to trade stock or other relatively opaque credit derivatives (e.g., Pagano and Röell, 1996; Loon and Zhang, 2014). Duffie and Zhu (2011) and Arora et al. (2012) also express doubts about the efficiency of CCP. Overall, the result supports Acharya and Johnson's (2007) argument that the CDS market may be driven largely by insider trading.

As for the four control variables, the results of RML and CCON are generally consistent with the findings of Forte and Lovreta (2015). When the liquidity of the CDS market is relatively higher than that of the stock market (high RML), the CDS market contributes more to credit risk discovery. Except for GIS, the credit quality of reference entity is positively associated with the credit risk discovery contribution of CDS. The negative coefficient of ADS3 imply that the adverse shocks are captured by the stock market first. Although downgrade is generally accompanied by a higher credit risk discovery contribution of the CDS market, the coefficient is insignificant. Forte and Lovreta (2015) find that downgrades and adverse shocks are discovered first by the CDS market. As they study the European firms from 2002 to 2008 and this chapter studies the U.S. firms from 2006 to 2013, the institutional differences, such as contract clauses and regulation policies, and different sample periods may explain, at least in part, the dissimilar results.

2.5.3 Robustness Test

To check the robustness of the results against the assumption that CDS and stock have a cointegration relation for all the firms in the sample, we conduct a sub-sample analysis of the drivers of credit risk discovery process by excluding the firms for which the two assets are not statistically cointegrated. As seen from Table 2.16 and 2.17, the general conclusions mostly mirror those drawn in the full sample analysis, especially when GIS measure is used. To be specific, CDS contributes more to credit risk discovery when the whole financial market suffers. A higher funding cost and a central clearing option weaken CDS's informational efficiency. The CDS market presents a higher credit risk discovery contribution when it is more liquid than the stock market. A firm's credit quality is positively related to its CDS's credit risk discovery ability. The stock market reacts more rapidly to adverse credit risk shocks. For downgrade events, the results in Table 2.17 reveal that their positive impact on CDS's credit risk discovery contribution becomes significant when BFCIUS is used as the proxy for the economy condition. Moreover, compared with the results of the full sample analysis, the impact of all the determinants is amplified for GIS, which is robust to LCS and CS. However, for IS and GG, no clear patterns can be observed. Overall, the results may provide further evidence to support that GIS measure is more robust, in contrast with IS and GG measures.

2.6 Conclusions

This chapter examines the dynamics and drivers of credit risk discovery between stock and CDS markets in the United States from 2006 to 2013. It employs an improved procedure to calculate credit risk discovery contribution and proposes new drivers of credit risk discovery process between CDS and stock, such as financial condition index and funding cost. The impact of the newly introduced central clearing counterparty on informational efficiency of the CDS market is also assessed.

CDS spreads and the implied credit spreads from the stock prices do not satisfy one-to-one cointegration, which is an essential assumption of Hasbrouck's (1995) information share (IS) and Gonzalo and Granger's (1995) component share (GG). This chapter addresses this issue by using the generalised information share (GIS) proposed by Lien and Shrestha (2014), which is free from the one-to-one cointegration assumption. The empirical results justify that GIS is a more suitable measure for credit risk discovery analysis between stock and CDS markets. When GIS is used, the relative informational dominance becomes much less extreme than when IS or GG is used. Nevertheless, on average, the three measures provide quantitatively consistent results. Stock generally leads CDS in credit risk discovery, except for the period of 2008–2010. Also, transitory components are eliminated from asset prices to obtain the pure credit risk component. This exercise increases the informational efficiency of the CDS market in the earlier sample period, possibly because the CDS market was less efficient back then. Another finding is that the CDS of investment-grade firms has a higher credit risk discovery contribution compared to that of speculative-grade firms.

Moreover, this chapter proposes financial condition index and funding cost as potential drivers of credit risk discovery, and they are both statistically significant. The results suggest that the credit risk discovery contribution of the stock market is generally higher but the CDS market becomes dominant when the overall economy is suffering. A higher funding cost adversely affects informational efficiency of the CDS market. Finally, it is not found that CCP can enhance the efficiency and transparency of the CDS market. Rather, CCP reduces the informational efficiency of the CDS market, which supports the insider trading hypothesis suggested by Acharya and Johnson (2007).

Table 2.1: Prediction of Credit Risk Discovery Function of Stock and CDS Markets

Hypothesis	Condition for Credit Risk Discovery Leadership	Dominant Market
Trading Cost Hypothesis	Low	Stock
Liquidity Hypothesis	High	Stock
Market Maturation Hypothesis	Mature	Stock
Firm-Specific Information Hypothesis/ Insider Trading Hypothesis	Negative firm-specific news	CDS
Market Trading Mechanism Hypothesis	Exchange and/or electronic trading	Stock

Notes: This table shows five price discovery hypotheses related to credit risk discovery. The conditions for leading the discovery of credit risk news are illustrated in the second column. Based on the inferences of these hypotheses, the expected dominant markets are presented in the third column. These hypotheses are not mutually exclusive and the dominant role of one market may result from the multiple influences of these hypotheses.

Table 2.2: Summary of Price Discovery Techniques

<table>
<tr><td>Group 1</td><td colspan="8">Lead – Lag Relation based on VAR Model, using returns</td></tr>
<tr><td>Group 2</td><td colspan="8">Volatility Spillover based on VAR-GARCH Model, using volatilities</td></tr>
<tr><td>Group 3</td><td colspan="8">Price Discovery Contribution Measures based on VECM Model, using prices</td></tr>
<tr><td></td><td></td><td>Provide unique result</td><td>Depend on one-to-one cointegraiton relation</td><td>Prefer high frequency data</td><td>Consider nonlinearity in adjustments to the long-run efficient price</td><td>It is dynamic</td><td>Permit long memory in equilibrium innovations</td><td>Consider the panel nature of the data</td></tr>
<tr><td></td><td colspan="8">Panel A: Price Discovery Contribution Measures Constructed in Reduced-form VECM Framework</td></tr>
<tr><td></td><td>Hasbrouck’s (1995) Information Share</td><td>No</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td>Lien and Shrestha’s (2009) Modified Information Share</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td>Lien and Shrestha’s (2014) Generalised Information Share</td><td>Yes</td><td>No</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td>Grammig and Peter’s (2013) New Information Share</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td>Gonzalo and Granger’s (1995) Component Share</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td>Figuerola-Ferretti and Gonzalo’s (2010) Component Share</td><td>Yes</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td colspan="8">Panel B: Price Discovery Contribution Measures Constructed in Structural VECM framework</td></tr>
<tr><td></td><td>Yan and Zivot’s (2010) New Information Share</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>No</td><td>No</td></tr>
<tr><td></td><td colspan="8">Panel C: Price Discovery Contribution Measures Constructed in Threshold VECM framework</td></tr>
<tr><td></td><td>Chen, Choi, and Hong’s (2013) Modified Component Share</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td></td><td colspan="8">Panel D: Price Discovery Contribution Measures Constructed in VECM-GARCH framework</td></tr>
</table>

	Avino, Lazar, Varotto (2015)'s Dynamic Information Share	No	Yes	Yes	No	Yes	No	No
	Panel E: Price Discovery Contribution Measures Constructed in Fractional VECM framework							
	Dolatabadi, Nielsen, and Xu's (2015) Modified Component Share	Yes	No	No	No	No	Yes	No
	Panel F: Price Discovery Contribution Measures Constructed in Panel VECM framework							
	Narayan, Sharma, and Thuraisamy's (2014) Panel Information Share/ Panel Component Share	No/Yes	Yes	Yes/ No	No	No	No	Yes

Notes: This table provides a summary of the extant price discovery methodologies. According to So and Tse (2004), price discovery methodologies can be classified into three groups. Group 1 is lead-lag relation based on VAR framework. Group 2 is volatility spillover based on VAR-GARCH Model. Group 3 is price discovery contribution measures based on VECM model. Panel A - F of Group 3 present the major price discovery contribution measures based on different VECM frameworks, as well as their characteristics.

Table 2.3: Summary of Empirical Findings of Credit Risk Discovery Determinants

Determinants	Previous Studies	Major Findings
Market Liquidity	Forte and Lovreta (2015)	For one market, higher market liquidity is accompanied with higher credit risk informational efficiency.
Credit Condition	Acharya and Johnson (2007); Forte and Lovreta (2015); Norden and Weber (2009)	Forte and Lovreta (2015) and Norden and Weber (2009) find that the worse credit condition of a firm is, the higher credit risk discovery contribution of stock market has. Acharya and Johnson (2007) suggest the opposite.
Number of Informed Insiders	Acharya and Johnson (2007)	The larger number of informed insiders is, the higher credit risk discovery contribution the CDS market has.
Hedging Demand	Marsh and Wagner (2015)	The higher hedging demand is, the longer lag CDS has to capture news.
Adverse Credit Shocks	Forte and Lovreta (2015); Norden and Weber (2004)	CDS market tends to incorporate adverse credit shocks first, compared with other credit-sensitive markets.
Credit Downgrades	Forte and Lovreta (2015); Wang and Bhar (2014); Norden (2017)	CDS market is more sensitive to credit downgrades events and impounds such information firstly.
Financial Crisis	Xiang, Chng, and Fang (2013); Avino, Lazar, and Varotto (2013); Narayan, Sharma, and Thuraisamy (2014); Forte and Lovreta (2015)	Extreme market conditions do affect different markets' information processing abilities. Certain market even can obtain price discovery leadership in the crisis times.
Earnings Announcements	Kryzanowski, Perrakis, and Zhong (2016); Hilscher, Pollet, and Wilson (2015)	CDS market's price discovery increases around earnings announcements, especially negative earnings surprises.
Transaction Costs	Hilscher, Pollet, and Wilson (2015)	High transaction costs slow down CDS in incorporating news.
Macroeconomic Announcements	Marsh and Wagner (2015); Kryzanowski, Perrakis, and Zhong (2016)	Marsh and Wagner (2015) find equity leads CDS when macro uncertainty is higher, while Kryzanowski et al. (2016) show that CDS market presents greater relative price discovery when either positive or negative macro news is announced.

Notes: This table summarises the previous empirical findings of the factors affecting credit risk discovery between CDS and stock markets.

Table 2.4: Data Sources

Category	Data	Source
CDS market	CDS quotes (<30/09/2010)	CMA from Datastream
	CDS quotes (≥30/09/2010)	Markit from TickHistory
Stock market	Stock prices	Bloomberg
	Market capitalization	
	Liabilities	
	Minority interests	
	Preferred shares	
Risk-free rate	5-year swap rate	Datastream
Firm characteristics	Credit rating	Compustat
	Industry classification	
Determinants	BFCIUS	Bloomberg
	GSFCI	Bloomberg
	3M CP and 3M T-bill	FRB reports
	CCP Clearing dates	ICE Clear Credit

Notes: This table summarizes the data required for the empirical analysis. CDS quotes are collected from two data sources as none of them covers the whole sample period.

Table 2.5: Summary Statistics of CS and ICS – By Years

	LCS				LICS			
	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
2006	50.04	83.97	0.20	976.41	112.23	154.54	0.32	1,240.10
2007	59.56	111.60	1.70	1,853.60	104.57	175.59	0.12	1,176.29
2008	169.10	323.15	13.00	10,210.71	187.64	273.37	0.27	2,907.39
2009	191.04	474.20	14.14	14,475.64	438.26	375.64	3.62	2,665.26
2010	123.67	116.28	21.26	780.94	150.54	186.05	0.58	1,176.62
2011	145.39	147.51	20.45	1,128.45	120.80	161.16	0.30	1,085.66
2012	162.03	223.63	15.20	2,427.62	149.17	192.75	0.15	1,372.41
2013	126.45	198.55	11.50	2,279.32	100.35	161.76	0.06	1,331.56
All	128.09	251.13	0.20	14,475.64	172.23	248.09	0.06	2,907.39
	CS				ICS			
	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
2006	50.72	84.77	2.50	987.50	63.30	119.91	0.37	1,232.66
2007	60.54	114.34	2.90	1,958.60	72.12	150.77	0.09	1,164.68
2008	171.40	338.09	15.50	11,095.00	198.07	280.98	0.28	2,946.19
2009	192.29	478.50	15.61	14,624.75	460.33	385.46	3.56	2,701.16
2010	123.77	116.95	20.50	793.07	158.55	188.68	0.59	1,181.32
2011	141.74	145.57	19.50	1,112.69	126.80	161.17	0.31	1,085.01
2012	157.10	215.96	11.50	2,259.00	155.51	193.68	1.10	1,373.11
2013	122.37	191.64	9.36	2,182.90	103.45	163.20	0.38	1,332.48
All	127.24	253.28	2.50	14,624.75	168.69	253.47	0.09	2,946.19

Notes: This table reports summary statistics of CS and ICS along the sample period. All the credit spreads are expressed in basis points.

Table 2.6: Summary Statistics of CS and ICS – By Credit Ratings

	LCS				LICS			
	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
AAA	26.17	18.03	0.20	117.39	17.80	27.32	0.32	152.88
AA	43.25	31.82	2.00	225.12	37.35	41.07	1.09	285.45
A	50.10	30.82	4.78	350.00	81.99	119.11	0.06	1,006.36
BBB	129.84	294.61	4.97	14,475.64	168.25	222.14	0.43	2,907.39
BB	252.68	181.89	25.00	1,697.53	310.11	320.53	0.29	1,590.63
B	520.96	589.18	24.80	12,033.19	691.81	334.93	39.48	2,093.80
CCC	452.14	517.47	35.70	2,427.62	313.29	219.43	37.98	899.65
	CS				ICS			
	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
AAA	25.81	18.10	2.50	115.00	22.71	27.15	0.68	152.51
AA	39.18	26.24	3.00	180.00	38.73	43.64	1.42	299.38
A	49.46	30.71	5.50	360.00	80.05	122.15	0.09	1,014.04
BBB	129.41	299.72	7.40	14,624.75	161.75	230.11	0.47	2,946.19
BB	252.91	183.79	26.50	1,717.03	333.26	349.85	7.58	1,958.61
B	517.54	576.74	26.50	11,877.19	658.68	322.05	37.42	1,373.11
CCC	434.96	492.23	34.20	2,259.00	339.11	238.00	24.95	926.29

Notes: This table reports summary statistics of CS and ICS across credit ratings. All the credit spreads are expressed in basis points.

Table 2.7: Augmented Dickey-Fuller (ADF) Unit-Root Test

	LCS	LICS	LCS-LICS
Levels	100 (88%)	111 (98%)	107 (95%)
First Differences	0 (0%)	0 (0%)	0 (0%)
	CS	ICS	CS-ICS
Levels	103 (91%)	112 (99%)	106 (94%)
First Differences	0 (0%)	0 (0%)	0 (0%)

Notes: This table summarises the results of the ADF unit-root tests on CS, ICS, and their difference, CS-ICS. Unit root test on CS-ICS is to test one-to-one cointegration of the pair. If the difference is non-stationary, one-to-one cointegration relationship is rejected. The figures are the number of non-stationary time series with their percentage values in parentheses. The significance level is 5%.

Table 2.8: Johansen Cointegration Test

	LCS-LICS	CS-ICS
Cointegration	68 (60%)	80 (71%)
No cointegration	45 (40%)	33 (29%)

Notes: This table summarises the results of the Johansen cointegration tests on LCS-LICS pairs and CS-ICS pairs. The figures in the first row are the number of firms for which cointegration is detected with their percentage values in parentheses. The significance level is 10%.

Table 2.9: The First Clearing Dates of Clearable Reference Entities

Ticker	Clearing Date	Ticker	Clearing Date	Ticker	Clearing Date
AA	23-Apr-2010	DOW	23-Apr-2010	LUV	02-Apr-2010
APA	26-Oct-2012	DRI	02-Apr-2010	MCK	03-Sep-2010
APC	12-Mar-2010	DVN	12-Mar-2010	MDC	01-Apr-2011
T	05-Feb-2010	F	02-Oct-2013	MO	12-Mar-2010
AVP	03-Oct-2013	FE	15-Jan-2010	MWV	04-Oct-2013
BAX	14-May-2010	GIS	13-Aug-2010	NSC	19-Feb-2010
BMY	14-May-2010	GPS	30-Sep-2013	NUE	05-Nov-2012
CAT	19-Feb-2010	HAL	12-Mar-2010	NWL	12-Mar-2010
CI	14-May-2010	HD	02-Apr-2010	OMC	03-Sep-2010
COP	13-Aug-2010	HON	19-Feb-2010	PBI	21-Jun-2011
CSX	19-Feb-2010	HPQ	23-Apr-2010	PFE	04-May-2011
CTL	05-Feb-2010	IBM	23-Apr-2010	PG	09-Nov-2012
DD	23-Apr-2010	JCI	13-Aug-2010	R	06-May-2011
DE	19-Feb-2010	LMT	19-Feb-2010	RAI	01-Apr-2011
DIS	02-Apr-2010	LOW	03-Sep-2010	SHW	19-Feb-2010
SRE	15-Jan-2010	TSN	15-Jun-2011	WHR	12-Mar-2010
SWY	02-Apr-2010	TXT	09-Nov-2012	WMB	07-Nov-2012
TGT	02-Apr-2010	UNP	19-Feb-2010	YUM	01-Apr-2011
TJX	03-Sep-2010	VFC	09-Nov-2012		

Notes: This table reports the first clearing dates of clearable CDS contracts and the tickers of the corresponding reference entities. The sample consists of 113 firms, and there are 56 firms' CDS contracts become clearable during the sample period 2006 – 2013.

Table 2.10: Credit Risk Discovery Contribution of CDS Market (LCS)

	GIS			IS			GG		
	GIS	>0.5	%	IS	>0.5	%	GG	>0.5	%
2006.2	0.53	63	56	0.50	61	54	0.50	59	52
2007.1	0.51	60	53	0.47	53	47	0.47	52	46
2007.2	0.48	53	47	0.38	36	32	0.36	29	26
2008.1	0.40	30	27	0.27	7	6	0.22	6	5
2008.2	0.39	28	25	0.37	19	17	0.33	17	15
2009.1	0.55	67	59	0.40	29	26	0.38	32	28
2009.2	0.49	48	42	0.42	35	31	0.40	34	30
2010.1	0.60	83	73	0.52	65	58	0.50	54	48
2010.2	0.50	60	53	0.40	37	33	0.30	19	17
2011.1	0.37	31	27	0.30	20	18	0.26	22	19
2011.2	0.42	40	35	0.36	23	20	0.28	16	14
2012.1	0.38	34	30	0.29	14	12	0.22	14	12
2012.2	0.38	29	26	0.31	22	19	0.25	19	17
2013.1	0.45	48	42	0.31	19	17	0.26	19	17
2013.2	0.34	24	21	0.25	8	7	0.16	7	6
All	0.45	35	31	0.37	9	8	0.33	8	7

Notes: This table reports the credit risk discovery contribution of CDS market measured by GIS, IS, and GG, using LCS and LICS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, and the last column is the number of firms converted into percentage.

Table 2.11: Credit Risk Discovery Contribution of CDS Market (CS)

	GIS			IS			GG		
	GIS	>0.5	%	IS	>0.5	%	GG	>0.5	%
2006.2	0.49	54	48	0.39	37	33	0.38	36	32
2007.1	0.45	51	45	0.33	24	21	0.30	25	22
2007.2	0.45	46	41	0.34	21	19	0.30	18	16
2008.1	0.39	29	26	0.27	5	4	0.22	4	4
2008.2	0.38	30	27	0.36	14	12	0.32	12	11
2009.1	0.54	68	60	0.42	32	28	0.40	39	35
2009.2	0.49	52	46	0.42	36	32	0.40	34	30
2010.1	0.61	84	74	0.53	67	59	0.51	65	58
2010.2	0.52	60	53	0.42	40	35	0.32	21	19
2011.1	0.36	25	22	0.31	16	14	0.27	21	19
2011.2	0.44	46	41	0.39	34	30	0.33	24	21
2012.1	0.40	36	32	0.32	20	18	0.24	14	12
2012.2	0.38	29	26	0.33	22	19	0.27	22	19
2013.1	0.47	51	45	0.33	22	19	0.27	19	17
2013.2	0.35	25	22	0.26	10	9	0.17	8	7
All	0.45	34	30	0.36	8	7	0.32	6	5

Notes: This table reports the credit risk discovery contribution of CDS market measured by GIS, IS, and GG, using CS and ICS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, and the last column is the number of firms converted into percentage.

Table 2.12: Credit Risk Discovery Contribution of Investment-Grade CDS versus Speculative-Grade CDS (LCS)

	Investment-Grade				Speculative-Grade			
	GIS	>0.5	%	Firms	GIS	>0.5	%	Firms
2006.2	0.54	53	56	94	0.50	10	53	19
2007.1	0.52	53	56	94	0.42	7	37	19
2007.2	0.48	44	47	94	0.49	9	47	19
2008.1	0.39	23	24	94	0.44	7	37	19
2008.2	0.39	26	28	94	0.35	2	11	19
2009.1	0.55	55	59	94	0.53	12	63	19
2009.2	0.50	40	43	94	0.44	8	42	19
2010.1	0.62	71	76	94	0.54	12	63	19
2010.2	0.50	50	53	94	0.50	10	53	19
2011.1	0.38	28	30	94	0.29	3	16	19
2011.2	0.42	33	35	94	0.41	7	37	19
2012.1	0.40	32	34	94	0.26	2	11	19
2012.2	0.38	25	27	94	0.35	4	21	19
2013.1	0.47	43	46	94	0.39	5	26	19
2013.2	0.33	19	20	94	0.39	5	26	19
All	0.46	32	34	94	0.42	3	16	19

Notes: This table compares the GIS measure of investment-grade CDS with that of speculative-grade CDS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, the third column is the number of firms converted into percentage, and the last column is the number of firms in each group. All calculations are based on the permanent price components, i.e., LCS and LICS.

Table 2.13: Credit Risk Discovery Contribution of CCP-Clearable CDS versus Non-Clearable CDS (LCS)

	CCP-Clearable				Non-Clearable			
	GIS	>0.5	%	Firms	GIS	>0.5	%	Firms
2010.1	0.59	23	72	32	0.61	60	74	81
2010.2	0.49	19	49	39	0.51	41	55	74
2011.1	0.40	16	35	46	0.34	15	22	67
2011.2	0.46	24	52	46	0.40	16	24	67
2012.1	0.42	17	37	46	0.35	17	25	67
2012.2	0.36	9	17	52	0.39	20	33	61
2013.1	0.47	26	50	52	0.44	22	36	61
2013.2	0.31	9	16	56	0.37	15	26	57

Notes: This table compares the GIS measure of CCP-clearable CDS with that of non-clearable CDS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, the third column is the number of firms converted into percentage, and the last column is the number of firms in each group. All calculations are based on the permanent price components, i.e., LCS and LICS.

Table 2.14: Determinants of Credit Risk Discovery (LCS)

	GIS		IS		GG	
BFCIUS	-1.21***		-1.64***		-1.54***	
	(0.00)		(0.00)		(0.00)	
GSFCI		4.07***		4.27***		4.78***
		(0.00)		(0.00)		(0.00)
FC	-4.23***	-2.51**	-5.31***	-2.55**	-5.10***	-2.79**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)
CCP	-7.98***	-5.52**	-11.21***	-8.67***	-15.50***	-12.62***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
RML	3.84**	2.96*	7.82***	6.65***	10.58***	9.47***
	(0.02)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
CCON	-0.00	-0.01	-0.01***	-0.02***	-0.02***	-0.02***
	(0.60)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)
ADS3	-23.92***	-24.39***	-29.82***	-29.13***	-33.70***	-33.91***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	1.43	1.02	2.79	2.37	3.71	3.22
	(0.52)	(0.65)	(0.18)	(0.25)	(0.11)	(0.16)
Constant	48.62***	49.14***	42.67***	43.05***	39.69***	40.25***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	1%	2%	3%	4%	4%	5%

Notes: This table reports the results of the panel regression (2.12).

$$y_{it} = \beta_0 + \beta_1 FCI_t + \beta_2 FC_t + \beta_3 CCP_{it} + \beta_4 RML_{it} + \beta_5 CCON_{it} + \beta_6 ADS3_{it} + \beta_7 CRDOWN_{it} + e_{it}$$

The dependent variable is either GIS, IS or GG of LCS. The independent variables are Bloomberg financial condition index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and CCP dummy (CCP), relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), and credit rating downgrades events (CRDOWN). Figures in parentheses are p-values. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 2.15: Determinants of Credit Risk Discovery (CS)

	GIS		IS		GG	
BFCIUS	-1.64***		-3.07***		-3.49***	
	(0.00)		(0.00)		(0.00)	
GSFCI		4.24***		5.13***		6.23***
		(0.00)		(0.00)		(0.00)
FC	-6.36***	-3.59***	-9.67***	-3.46***	-10.97***	-4.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCP	-5.21***	-2.69	-6.62***	-3.72**	-9.38***	-5.82***
	(0.00)	(0.14)	(0.00)	(0.03)	(0.00)	(0.00)
RML	2.23*	1.07	2.67**	0.52	5.17***	2.73
	(0.06)	(0.39)	(0.03)	(0.69)	(0.00)	(0.12)
CCON	-0.00	-0.00	-0.01***	-0.02***	-0.02***	-0.02***
	(0.71)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
ADS3	-20.91***	-20.20***	-27.04***	-22.56***	-28.63***	-24.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	0.18	-0.24	2.62	2.17	3.49	2.93
	(0.93)	(0.91)	(0.16)	(0.25)	(0.10)	(0.17)
Constant	48.07***	48.45***	41.30***	41.29***	38.08***	38.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	1%	2%	2%	3%	3%	4%

Notes: This table reports the results of the panel regression (2.12).

$$y_{it} = \beta_0 + \beta_1 FCI_t + \beta_2 FC_t + \beta_3 CCP_{it} + \beta_4 RML_{it} + \beta_5 CCON_{it} + \beta_6 ADS3_{it} + \beta_7 CRDOWN_{it} + e_{it}$$

The dependent variable is either GIS, IS or GG of CS. The independent variables are Bloomberg financial condition index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and CCP dummy (CCP), relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), and credit rating downgrades events (CRDOWN). Figures in parentheses are p-values. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 2.16: Determinants of Credit Risk Discovery – Sub-sample Analysis (LCS)

	GIS		IS		GG	
BFCIUS	-1.57***		-1.35**		-1.22**	
	(0.00)		(0.01)		(0.02)	
GSFCI		4.62***		3.56***		4.21***
		(0.00)		(0.00)		(0.00)
FC	-5.44***	-3.02**	-3.57**	-1.35	-2.39	-0.70
	(0.00)	(0.01)	(0.04)	(0.21)	(0.22)	(0.59)
CCP	-10.16***	-7.47***	-9.68***	-7.61***	-15.28***	-12.81***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RML	5.77**	4.58**	9.75***	8.72***	14.86***	13.94***
	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
CCON	-0.00	-0.00	-0.00	-0.01*	-0.00	-0.01*
	(0.75)	(0.67)	(0.13)	(0.06)	(0.24)	(0.09)
ADS3	-31.22***	-31.06***	-40.05***	-39.36***	-49.90***	-50.60***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	3.72	2.75	3.53	2.80	4.22	3.30
	(0.34)	(0.48)	(0.18)	(0.29)	(0.16)	(0.28)
Constant	47.13***	47.74***	37.07***	37.49***	31.01***	31.65***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	1%	3%	3%	4%	4%	6%

Notes: This table reports the results of the panel regression (2.12).

$$y_{it} = \beta_0 + \beta_1 FCI_t + \beta_2 FC_t + \beta_3 CCP_{it} + \beta_4 RML_{it} + \beta_5 CCON_{it} + \beta_6 ADS3_{it} + \beta_7 CRDOWN_{it} + e_{it}$$

When LCS are used, 68 pairs of LCS-LICS are statistically cointegrated. The dependent variable is either GIS, IS or GG of LCS. The independent variables are Bloomberg financial condition index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and CCP dummy (CCP), relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), and credit rating downgrades events (CRDOWN). Figures in parentheses are p-values. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 2.17: Determinants of Credit Risk Discovery – Sub-sample Analysis (CS)

	GIS		IS		GG	
BFCIUS	-1.73***		-2.94***		-3.40***	
	(0.00)		(0.00)		(0.00)	
GSFCI		4.40***		4.83***		5.97***
		(0.00)		(0.00)		(0.00)
FC	-7.05***	-4.20***	-9.64***	-3.81***	-11.06***	-4.45***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCP	-5.86**	-3.33	-7.23***	-4.57**	-10.55***	-7.24***
	(0.01)	(0.12)	(0.00)	(0.02)	(0.00)	(0.00)
RML	2.90**	1.31	2.96*	0.57	5.87***	3.05
	(0.03)	(0.38)	(0.06)	(0.72)	(0.00)	(0.15)
CCON	-0.00	-0.01	-0.02**	-0.02**	-0.03**	-0.03**
	(0.79)	(0.43)	(0.04)	(0.02)	(0.01)	(0.01)
ADS3	-23.13***	-21.88***	-28.56***	-23.53***	-31.70***	-26.30***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	4.96*	4.49	4.80*	4.27	5.34*	4.69
	(0.07)	(0.12)	(0.07)	(0.10)	(0.09)	(0.13)
Constant	49.04***	49.79***	40.73***	40.92***	38.03***	38.41***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	1%	2%	2%	3%	3%	4%

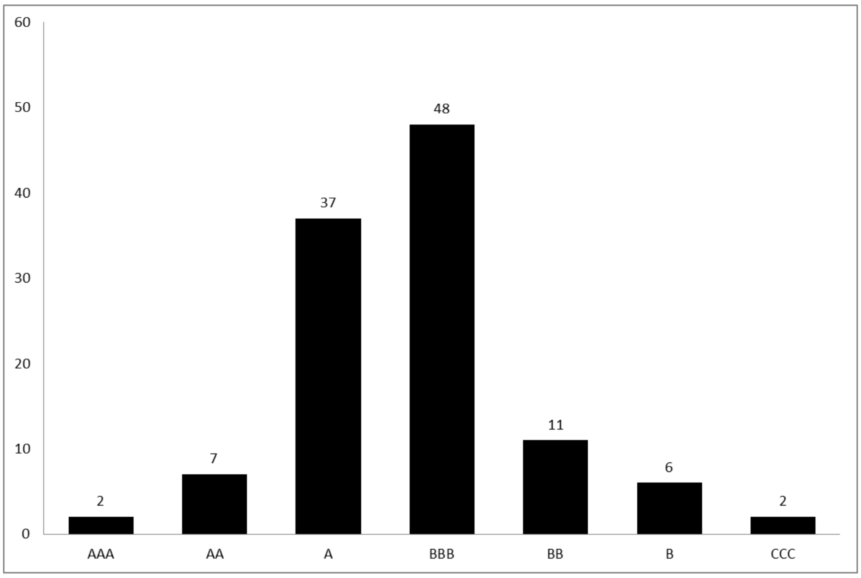
Notes: This table reports the results of the panel regression (2.12).

$$y_{it} = \beta_0 + \beta_1 FCI_t + \beta_2 FC_t + \beta_3 CCP_{it} + \beta_4 RML_{it} + \beta_5 CCON_{it} + \beta_6 ADS3_{it} + \beta_7 CRDOWN_{it} + e_{it}$$

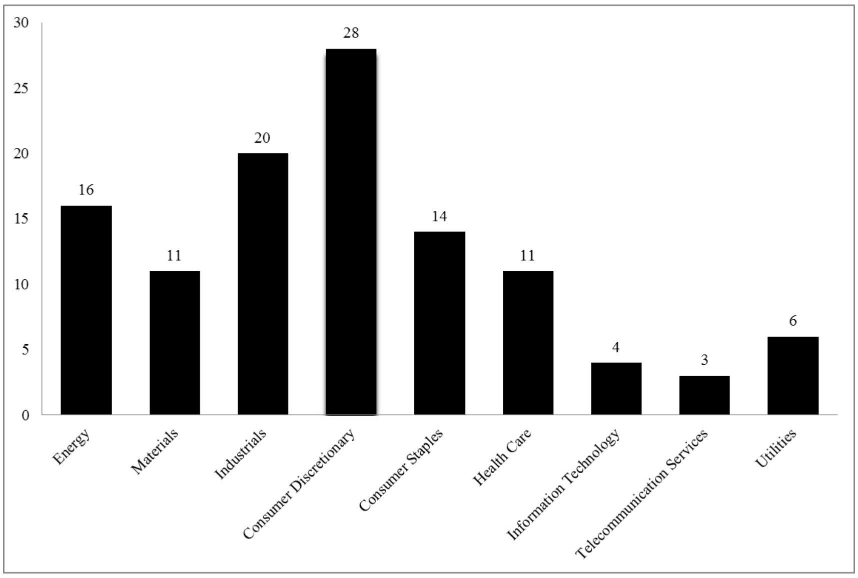
When CDS are used, 80 pairs of CS-ICS are statistically cointegrated. The dependent variable is either GIS, IS or GG of LCS. The independent variables are Bloomberg financial condition index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and CCP dummy (CCP), relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), and credit rating downgrades events (CRDOWN). Figures in parentheses are p-values. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Figure 2.1: Distribution of Sample Firms

Panel A: Distribution of Firms across Credit Ratings



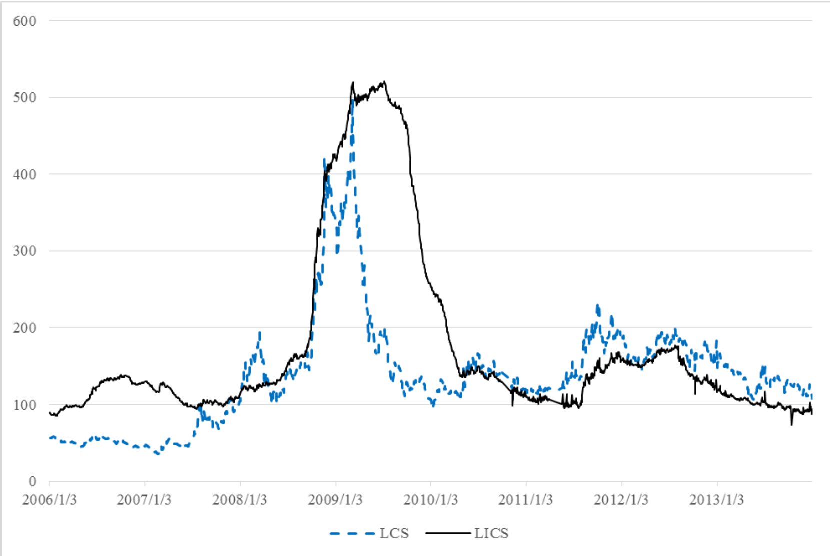
Panel B: Distribution of Firms across Industry Sectors



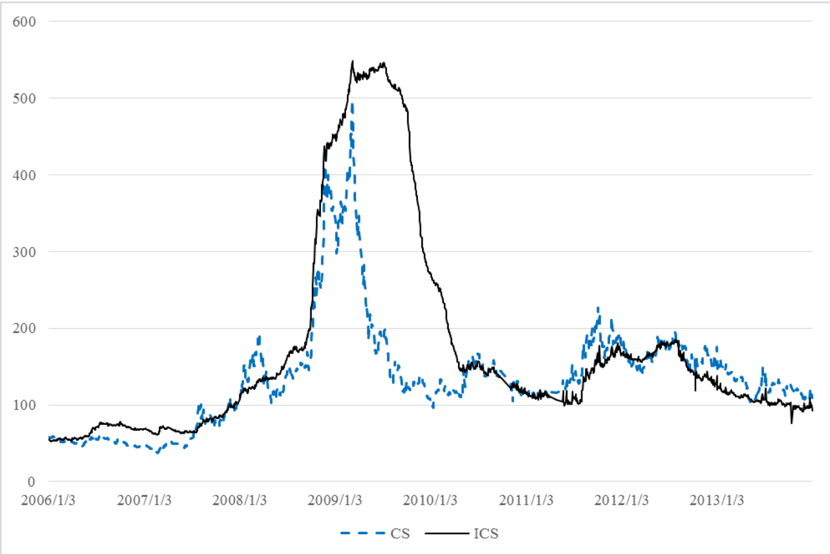
Notes: This figure illustrates credit ratings and industry sectors of the 113 firms in the sample. Credit ratings are based on the S&P Domestic Long Term Issuer Credit Ratings as of 31/12/2013 and industry classifications are based on the Global Industry Classification Standard. Panel A is based on credit ratings and Panel B is based on industry sectors.

Figure 2.2: Cross-Sectional Means of CDS (LCS) and ICS (LICS)

Panel A: Cross-Sectional Means of LCS and LICS

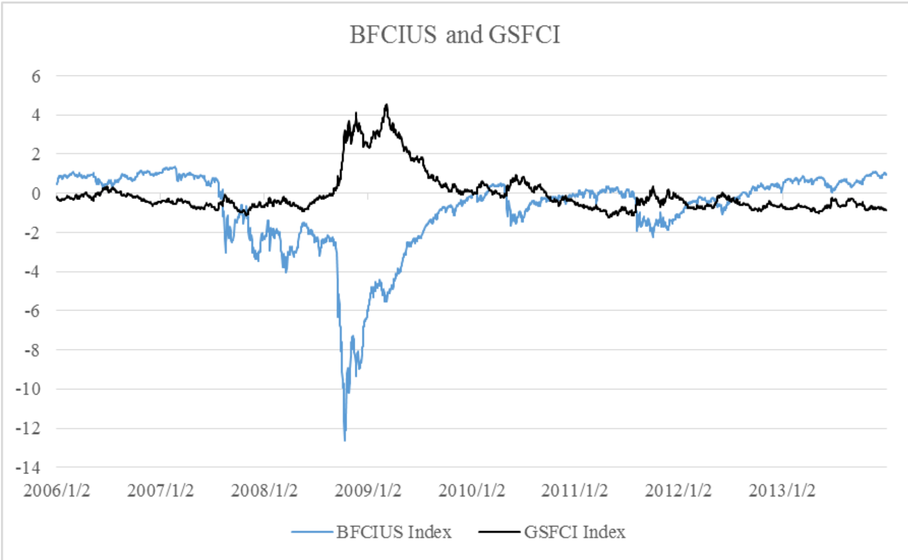


Panel B: Cross-Sectional Means of CS and ICS



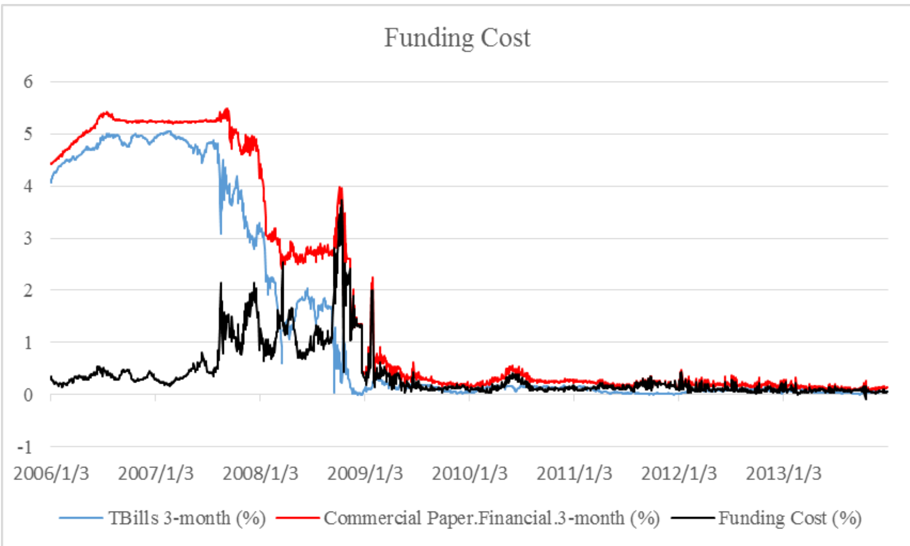
Notes: Panel A of this figure plots the cross-sectional means of LCS and LICS and Panel B plots the cross-sectional means of CS and ICS. The sample period is from January 2006 to December 2013. All the credit spreads are expressed in basis points.

Figure 2.3: The U.S. Financial Condition Index



Notes: This figure plots the U.S. Bloomberg Financial Condition Index and the U.S. Goldman Sachs Financial Condition Index from 01/01/2006 to 31/12/2013. The lower (higher) BFCIUS (GSFCI) indicates the higher systemic risk in the U.S. financial market.

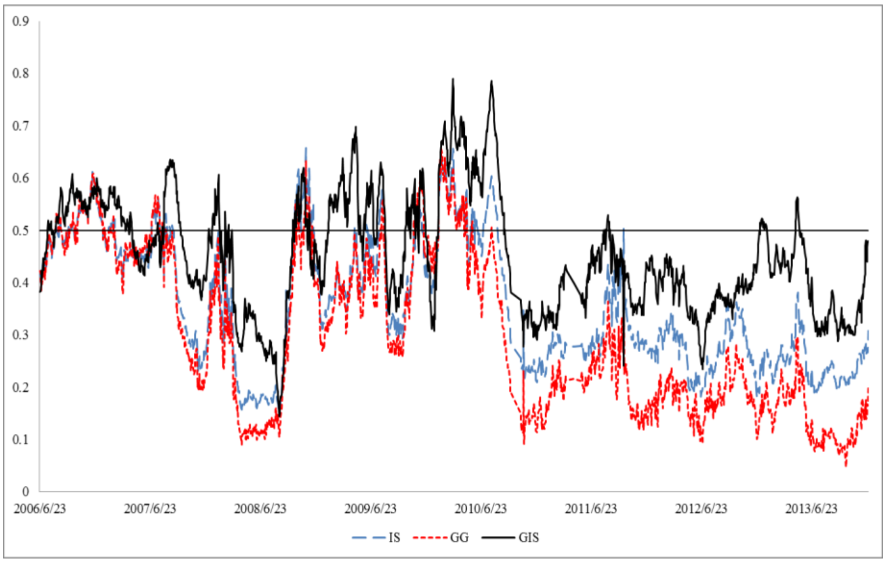
Figure 2.4: The Overall Funding Cost in the U.S.



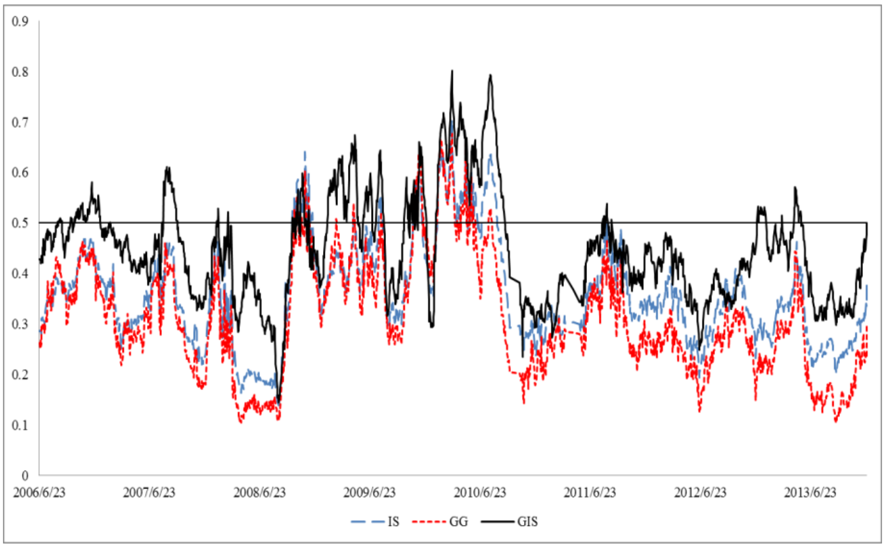
Notes: This figure plots the interest rates of 3-month financial commercial paper, the interest rates of 3-month T-bill, and the differences between two rates which is the proxy of the overall funding cost in the U.S. market. The sample period is 01/01/2006-31/12/2013. All the rates are expressed in percentage (%).

Figure 2.5: Credit Risk Discovery Contribution of the CDS Market

Panel A: Credit Risk Discovery Contribution of LCS



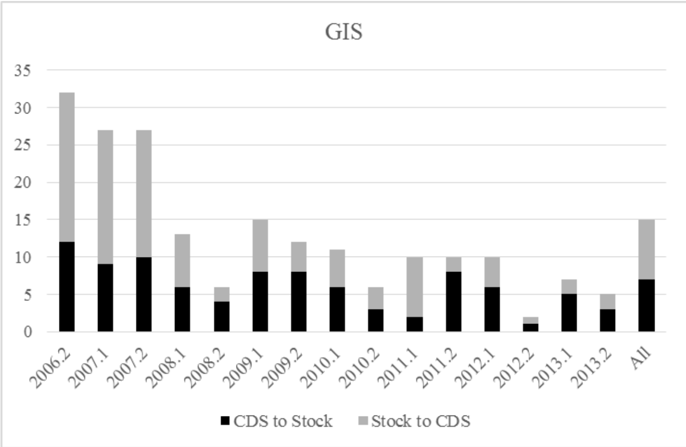
Panel B: Credit Risk Discovery Contribution of CS



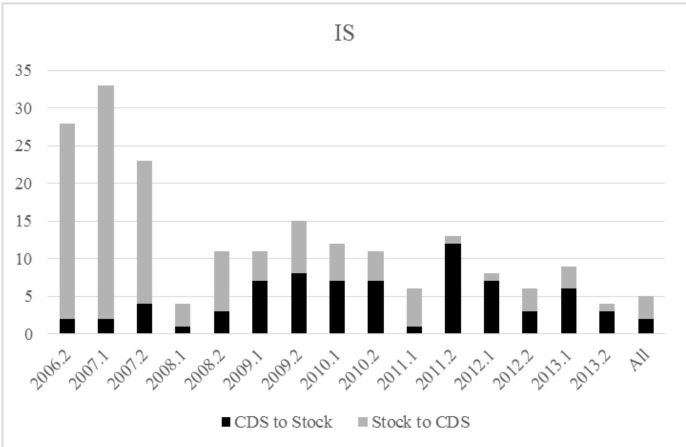
Notes: This figure plots the cross-sectional means of credit risk discovery contribution of the CDS market measured by GIS, IS, and GG from mid-2006 to 2013. The upper graph is based on the permanent price components (LCS and LICS) and the lower graph is based on the original prices (CS and ICS).

Figure 2.6: Impact of Transitory Components on Credit Risk Discovery Leadership

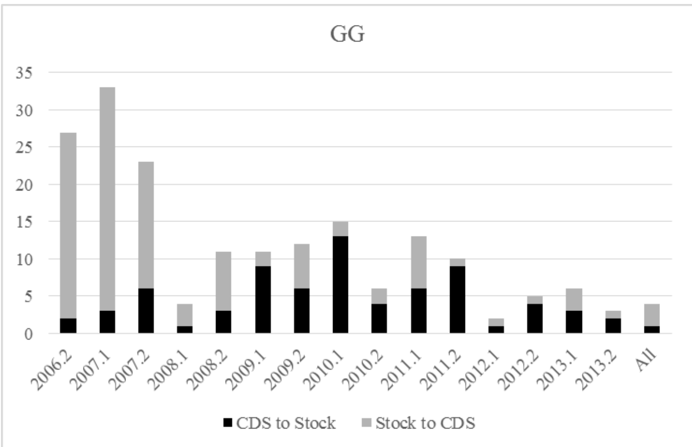
Panel A: Lien and Shrestha's (2014) Generalized Information Share (GIS)



Panel B: Hasbrouck's (1995) Information Share (IS)

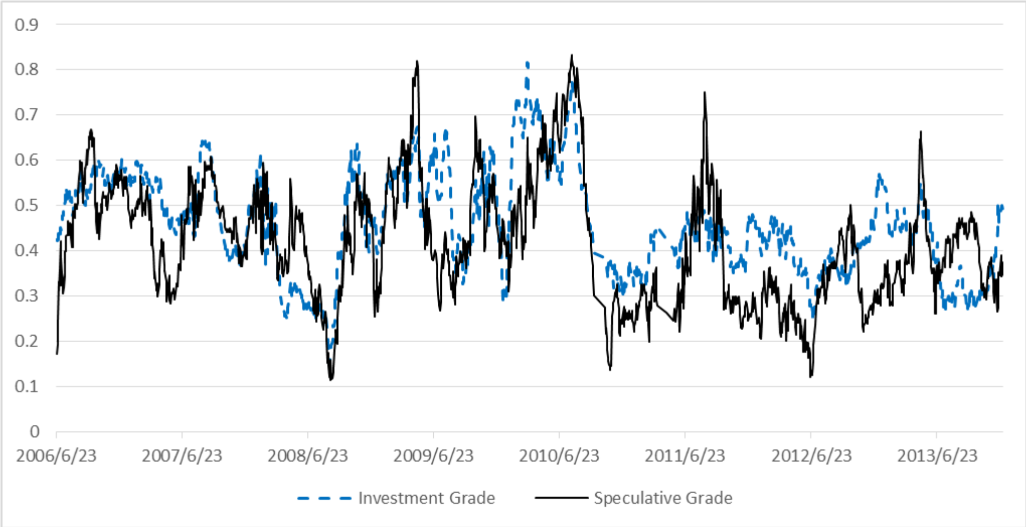


Panel C: Gonzalo and Granger's (1995) Component Share (GG)



Notes: This chart shows the number of firms for which the credit risk discovery leadership is reversed after eliminating transitory components. 'CDS to Stock' refers to the firms for which the leadership has moved from CDS to stock and 'Stock to CDS' refers to the opposite case.

Figure 2.7: Credit Risk Discovery Contribution of Investment-Grade CDS versus Speculative-Grade CDS



Notes: This figure plots the cross-sectional means of GIS for investment-grade CDS and GIS for speculative-grade CDS. All calculations are based on the permanent price components, i.e., LCS and LICS.

Appendix 2A: The CreditGrades Model and the Calculation of ICS

According to Finger et al. (2002), CreditGrades model introduces randomness to default barrier although the distribution of default barrier is time-invariant. Also, in comparison with other structural credit risk models, CreditGrades model is more practical and easier for implementation as it links most of the model parameters, e.g., asset value and asset volatility, to market observables (Xiang et al., 2013). To extract implied credit spreads from equity market, survival probability is calculated first and then survival probability is converted to stock implied credit spreads. The first step is to obtain survival probability. Asset value V_t (on a per share basis) follows a Geometric Brownian Motion:

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt \tag{A.1}$$

where W_t is a standard Brownian motion and has the distribution $W_t \sim N(0, t)$. σ is the asset volatility. μ_D is the expected asset mean and is assumed to be zero. Default barrier is defined as the amount of the firm's assets remaining when default occurs, which equals the recovery value that the debt holders receive, $L \cdot D$, where L is the average recovery on the debts and D is the firm's debt-per-share. Assume the recovery rate L to follow a lognormal distribution with mean $\bar{L}$ and percentage standard deviation λ.

$$\bar{L} = EL, \lambda^2 = Var(log\, L), LD = \bar{L}De^{\lambda Z - \lambda^2/2} \tag{A.2}$$

where $Z \sim N(0,1)$ and Z is independent of the Brownian motion W_t. Z is unknown until the time of default. For an initial asset value V_0, default occurs once:

$$V_0 e^{\sigma W_t - \sigma^2 t/2} \leq \bar{L}De^{\lambda Z - \lambda^2/2} \tag{A.3}$$

The survival probability of the company at time t is given by the probability that the asset value does not touch the default barrier before time t. Denote a process X_t,

$X_t = \sigma W_t - \frac{\sigma^2 t}{2} - \lambda Z - \frac{\lambda^2}{2}, and\ X_t > log\left(\frac{\bar{L}D}{V_0}\right) - \lambda^2$, when $t \geq 0$, X_t is normally distributed: $X_t \sim N\left(-\frac{\sigma^2 t}{2} - \frac{\lambda^2}{2}, \sigma^2 t + \sigma^2 \lambda^2\right)$.

A closed-form formula for the survival probability up to time t,

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d \cdot \Phi(-\frac{A_t}{2} - \frac{log(d)}{A_t}) \quad \text{(A.4)}$$

where $\Phi(\cdot)$ is the cumulative distribution function, $d = \frac{V_0}{\bar{L}D} e^{\lambda^2}$ and $A_t^2 = \sigma^2 t + \lambda^2$.

Then, the survival probability is converted to a credit spread. To price a CDS contract, let $f(t)$ be the density function of default time, $f(t) = -\frac{dP(t)}{dt}$. Thus, the cumulative default probability up to time t is $1 - P(0) + \int_0^t \mathrm{d}s f(s)$. For a CDS contract with maturity t and a continuous spread ICS, the present value of expected loss compensations for the CDS is:

$$(1 - R)\left[1 - P(0) + \int_0^t f(s) \cdot e^{-rs}\, ds\right] \quad \text{(A.5)}$$

where r is the risk free interest rate and R is the recovery rate on the specific underlying debt. R is different from $\bar{L}$ because R is the expected recovery rate on a specific class of the firm's debt, while $\bar{L}$ is the expected recovery rate averaged over all debt classes. The asset-specific recovery rate R for an unsecured debt is usually lower than $\bar{L}$ since the secured debt would have a higher recovery rate.

The present value of expected CDS spread payments because of a default event is:

$$ICS \int_0^t P(s) \cdot e^{-rs} ds \quad \text{(A.6)}$$

The price of CDS is the difference between discounted spread and loss compensation:

$$CDS = (1-R)\left[1 - P(0) + \int_0^t f(s) \cdot e^{-rs}\, ds\right] - ICS \int_0^t P(s) \cdot e^{-rs} ds \qquad \text{(A.7)}$$

To ensure at time 0, the value of CDS contract is zero. We have the following equation:

$$(1-R)\big(1-P(0)\big) - \left(\frac{ICS}{r}\right)\left(P(0) - P(t)e^{-rt}\right) = -\left(1 - R + \frac{ICS}{r}\right) e^{r\xi}[G(t+\xi) - G(\xi)]$$

with $\xi = \frac{\lambda^2}{\sigma^2}$, $G(t) = d^{z+\frac{1}{2}}\, \Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + d^{-z+\frac{1}{2}}\, \Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right)$, and $z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma^2}}$. Therefore, the closed-form solution for ICS can be obtained:

$$ICS = r(1-R)\left[\frac{1-P(0)+H(t)}{P(0)-P(t)e^{-rt}-H(t)}\right],\ with\ H(t) = e^{r\xi}(G(t+\xi) - G(\xi)) \qquad \text{(A.8)}$$

Appendix 2B: Unite-Root Test Results

Table 2B.1: Unit-Root Test Results of LCS (CS) and LICS (ICS)

Panel A: Unit-Root test results of LCS and LICS			
Ticker	LCS	LICS	One-to-one relation of LCS and LICS
MMM	-1.898	-1.37	-2.348
ABT	-1.772	-3.167*	-3.594**
AA	-2.044	-1.245	-1.67
MO	-1.788	-1.153	-2.007
ABC	-1.337	-1.159	-1.564
APC	-2.505	-1.437	-1.451
APA	-3.101**	-1.591	-1.564
T	-2.451	-1.073	-2.056
AVP	-1.314	-2.304	-2.354
BAX	-2.349	-2.498	-2.679
BZH	-2.794	-2.018	-3.151*
BMY	-2.529	-1.151	-1.589
CA	-3.352**	-1.083	-2.157
CAT	-2.653	-1.348	-1.246
CNP	-1.675	-1.122	-1.24
CTL	-1.912	-2.165	-1.83
CHK	-2.409	-1.458	-1.878
CI	-2.728	-1.281	-1.192
CLX	-1.841	-0.928	-1.662
CMC	-1.861	-1.288	-1.113
CNF	-2.411	-1.295	-1.576
COP	-2.324	-1.731	-1.572
ED	-2.122	-1.254	-1.595
COST	-2.224	-1.269	-1.773
CSX	-2.148	-1.037	-1.538
CVS	-2.77	-1.504	-1.684
DHR	-1.818	-1.443	-1.983
DRI	-2.226	-1.29	-1.059
DE	-2.531	-1.078	-0.928
DVN	-2.572	-1.329	-1.243
D	-3.248**	-1.349	-2.055
DOV	-1.901	-1.228	-1.391
DOW	-2.444	-0.975	-1.761
DHI	-2.468	-0.914	-1.139
DD	-2.562	-1.234	-1.241
LLY	-1.696	-1.481	-1.604
EEP	-1.962	-1.219	-1.752
ETR	-1.753	-1.358	-2.083
EPD	-2.022	-1.09	-1.802
XOM	-2.068	-1.701	-2.138
FE	-2.14	-1.288	-1.597
F	-2.681	-0.984	-3.358*
GCI	-2.113	-1.036	-2.65
GPS	-1.817	-1.517	-1.531
GD	-2.597	-1.641	-2.193
GIS	-2.658	-1.210	-2.293
HAL	-2.707	-1.375	-1.364
HAS	-1.879	-1.519	-1.778

HMA	-1.893	-1.524	-1.833
HES	-2.129	-1.588	-1.558
HPQ	-1.441	-1.082	-1.471
HD	-2.016	-1.044	-1.537
HON	-2.368	-1.296	-1.293
IBM	-2.897**	-1.284	-2.614
JCP	-0.979	-0.327	-1.613
JNJ	-1.905	-1.633	-2.314
JCI	-2.568	-1.362	-1.894
KBH	-2.42	-1.716	-1.487
K	-1.933	-1.927	-1.837
KMB	-1.812	-1.171	-1.713
LMT	-2.321	-1.228	-1.466
LOW	-2.308	-1.403	-1.577
MAR	-2.007	-0.962	-1.861
MAS	-2.133	-1.112	-1.633
MCK	-3.157**	-3.417*	-3.374*
MDC	-2.567	-1.326	-1.262
MWV	-2.226	-1.166	-1.238
MDT	-1.973	-1.879	-2.311
MUR	-2.31	-1.546	-1.629
NWL	-1.891	-0.849	-1.034
NEM	-1.636	-1.457	-1.723
NSC	-3.336**	-1.24	-1.656
NUE	-2.425	-1.188	-1.035
OXY	-2.406	-1.603	-1.438
OLN	-3.682***	-1.177	-1.534
OMC	-2.841	-1.446	-3.433*
OKE	-2.592	-1.429	-1.302
PKG	-2.864**	-1.091	-1.32
PFE	-1.926	-1.36	-2.588
PBI	-1.428	-1.557	-1.59
PG	-1.792	-1.282	-1.956
PHM	-2.381	-0.822	-0.889
RSH	-0.488	-0.454	-1.025
RTN	-2.561	-1.49	-2.117
RSG	-1.694	-1.815	-2.184
RAI	-2.111	-0.863	-2.435
R	-2.065	-1.166	-1.226
RYL	-2.22	-1.732	-1.472
SWY	-1.455	-1.65	-1.855
SRE	-2.913**	-1.404	-1.797
SHW	-3.277**	-1.113	-2.078
LUV	-2.494	-0.897	-2.231
SPF	-2.283	-1.133	-3.318*
SVU	-1.835	-2.859	-2.627
TGT	-2.285	-1.27	-1.036
TSO	-2.106	-0.914	-1.486
TXN	-2.828	-1.352	-2.292
TXT	-2.511	-1.041	-2.023
NYT	-1.981	-1.08	-1.932
TWX	-2.619	-1.243	-1.508
TJX	-2.213	-1.324	-1.469
TSN	-2.602	-0.949	-1.261
UNP	-2.956**	-0.961	-1.077

X	-1.835	-1.374	-1.549
UTX	-2.316	-1.487	-1.932
VLO	-2.03	-1.356	-1.21
VZ	-3.112**	-1.271	-2.275
VFC	-2.733	-1.24	-1.626
WMT	-1.913	-1.731	-2.241
DIS	-2.687	-1.152	-1.352
WHR	-2.26	-1.145	-1.125
WMB	-3.789***	-1.591	-1.205
YUM	-2.341	-0.920	-1.231
Panel B: Unit-Root test results of CS and ICS			
Ticker	CS	ICS	One-to-one relation of CS and ICS
MMM	-1.885	-1.212	-2.188
ABT	-1.783	-2.943**	-3.771***
AA	-2.125	-1.611	-1.703
MO	-1.763	-0.957	-1.538
ABC	-1.347	-1.179	-0.810
APC	-2.544	-1.631	-1.665
APA	-3.142**	-1.603	-1.576
T	-2.473	-1.161	-2.028
AVP	-1.303	-2.221	-2.342
BAX	-2.323	-2.076	-2.085
BZH	-2.735	-2.036	-3.091**
BMY	-2.5	-1.055	-1.706
CA	-3.307**	-1.13	-2.032
CAT	-2.703	-1.171	-1.029
CNP	-1.653	-1.478	-1.712
CTL	-1.964	-1.952	-2.003
CHK	-2.421	-1.462	-1.835
CI	-2.8	-1.265	-1.248
CLX	-1.87	-0.900	-1.817
CMC	-1.848	-1.209	-1.067
CNF	-2.434	-1.252	-1.571
COP	-2.309	-1.588	-1.517
ED	-2.09	-1.2	-1.719
COST	-2.216	-1.277	-1.848
CSX	-2.108	-1.021	-1.471
CVS	-2.809	-1.455	-1.692
DHR	-1.818	-1.458	-2.041
DRI	-2.24	-1.239	-0.995
DE	-2.571	-1.157	-1.006
DVN	-2.629	-1.357	-1.302
D	-3.207**	-1.33	-2.042
DOV	-1.882	-1.178	-1.366
DOW	-2.497	-0.950	-1.626
DHI	-2.442	-0.901	-0.932
DD	-2.592	-1.229	-1.197
LLY	-1.711	-1.499	-1.618
EEP	-1.953	-1.269	-1.943
ETR	-1.728	-1.388	-2.123
EPD	-2.035	-1.137	-1.972
XOM	-2.062	-1.7	-2.195
FE	-2.179	-1.324	-1.563
F	-2.622	-0.948	-3.313**
GCI	-2.1	-1.038	-2.688

GPS	-1.81	-1.468	-1.529
GD	-2.633	-1.578	-2.171
GIS	-2.592	-1.199	-2.434
HAL	-2.718	-1.436	-1.422
HAS	-1.899	-1.474	-1.793
HMA	-1.891	-1.681	-2.122
HES	-2.126	-1.485	-1.301
HPQ	-1.464	-1.082	-1.434
HD	-1.997	-1.058	-1.554
HON	-2.356	-1.322	-1.351
IBM	-2.859	-1.269	-2.786
JCP	-1.089	-0.457	-1.691
JNJ	-1.859	-1.621	-2.573
JCI	-2.603	-1.138	-3.203**
KBH	-2.442	-2.036	-1.907
K	-1.979	-1.718	-2.165
KMB	-1.808	-1.168	-1.764
LMT	-2.373	-1.189	-1.428
LOW	-2.293	-1.382	-1.548
MAR	-1.993	-1.09	-1.848
MAS	-2.122	-1.041	-1.576
MCK	-3.086**	-1.298	-1.406
MDC	-2.625	-1.2	-1.121
MWV	-2.246	-1.123	-1.126
MDT	-1.954	-1.808	-2.262
MUR	-2.295	-1.479	-1.54
NWL	-1.926	-0.852	-1.033
NEM	-1.675	-1.24	-1.588
NSC	-3.224**	-1.18	-1.588
NUE	-2.462	-1.249	-1.1
OXY	-2.457	-1.643	-1.49
OLN	-3.747***	-1.142	-1.323
OMC	-2.821	-1.409	-3.366**
OKE	-2.637	-1.583	-1.414
PKG	-2.869**	-1.097	-1.137
PFE	-1.938	-1.353	-2.25
PBI	-1.445	-1.504	-1.611
PG	-1.748	-1.268	-2.143
PHM	-2.385	-0.917	-0.904
RSH	-0.412	-0.494	-0.99
RTN	-2.576	-1.432	-2.107
RSG	-1.747	-1.691	-2.083
RAI	-2.1	-0.906	-2.857
R	-2.075	-1.157	-1.176
RYL	-2.207	-1.479	-1.408
SWY	-1.471	-1.274	-1.606
SRE	-2.853	-1.368	-1.775
SHW	-3.273**	-1.073	-2.035
LUV	-2.483	-1.108	-2.15
SPF	-2.296	-1.208	-3.442***
SVU	-1.83	-2.317	-2.865**
TGT	-2.265	-1.319	-1.065
TSO	-2.087	-0.975	-1.338
TXN	-2.837	-1.368	-2.225
TXT	-2.448	-1.021	-1.786

NYT	-1.991	-0.935	-1.847
TWX	-2.578	-1.225	-1.473
TJX	-2.206	-1.107	-1.615
TSN	-2.538	-1.085	-1.579
UNP	-2.845	-0.948	-1.061
X	-1.882	-1.395	-1.618
UTX	-2.347	-1.483	-1.915
VLO	-2.02	-1.405	-1.26
VZ	-3.094**	-1.265	-2.294
VFC	-2.726	-1.218	-1.551
WMT	-1.898	-1.694	-2.403
DIS	-2.647	-1.185	-1.371
WHR	-2.304	-1.128	-1.123
WMB	-3.747***	-1.778	-1.287
YUM	-2.307	-0.924	-1.25

Notes: This table reports the results of the ADF Unit-Root Tests on LCS (CS) and LICS (ICS). The stock ticker of each reference entity in our sample is in the first column. The critical value is -2.863 at 5% and -3.437 at 1% level of significance, respectively. ** and *** indicate the test statistic to be significant at 5% and 1%, respectively. For the test of one-to-one cointegration, as Lien and Shrestha (2014) do, the difference between LCS (CS) and LICS (ICS) is calculated. If the difference is non-stationary, then the one-to-one cointegrating relationship can be rejected. The results show that even after eliminating transitory effects from credit spreads, the one-to-one cointegrating assumption cannot obtain in most cases.

Table 2B.2: Unit-Root Test Results of the First-Differences of LCS (CS) and LICS (ICS)

Panel A: Unit-Root test results of the first-differences of LCS and LICS			
Ticker	LCS	LICS	One-to-one relation of LCS and LICS
MMM	-11.04***	-9.787***	-9.836***
ABT	-12.93***	-13.25***	-13.25***
AA	-12.41***	-7.237***	-11.94***
MO	-9.007***	-10.07***	-8.928***
ABC	-10.63***	-8.204***	-10.51***
APC	-9.694***	-8.414***	-9.347***
APA	-12.98***	-9.485***	-10.43***
T	-13.24***	-8.252***	-12.1***
AVP	-12.5***	-12.08***	-12.34***
BAX	-13.25***	-13.09***	-13.5***
BZH	-14.39***	-10.19***	-14.33***
BMY	-12.28***	-12.3***	-12.2***
CA	-11.16***	-10.02***	-11.18***
CAT	-12.23***	-9.939***	-12.7***
CNP	-9.938***	-9.319***	-9.958***
CTL	-14.4***	-11.73***	-12.83***
CHK	-13.15***	-7.823***	-11.88***
CI	-11.95***	-6.956***	-8.158***
CLX	-12.11***	-11.77***	-12.09***
CMC	-11.43***	-8.37***	-10.14***
CNF	-12.56***	-10.25***	-11.79***
COP	-13.92***	-7.666***	-9.3***
ED	-10.83***	-10.48***	-11.6***
COST	-11.79***	-10.75***	-12***
CSX	-13.45***	-11.17***	-9.963***
CVS	-11.83***	-12.88***	-13.01***
DHR	-11.84***	-10.47***	-12.01***
DRI	-13.97***	-10.33***	-13.67***
DE	-12.14***	-6.895***	-7.948***
DVN	-13.07***	-10.75***	-11.29***
D	-13.25***	-9.25***	-12.58***
DOV	-11.57***	-9.254***	-8.843***
DOW	-11.17***	-9.815***	-11.01***
DHI	-13.05***	-8.893***	-11.57***
DD	-12.86***	-9.13***	-11.36***
LLY	-12.5***	-10.43***	-10.91***
EEP	-9.194***	-9.94***	-10.48***
ETR	-12.06***	-9.05***	-12.25***
EPD	-10.62***	-9.438***	-10.73***
XOM	-11.48***	-9.465***	-11.25***
FE	-13.04***	-9.104***	-10.6***
F	-12.28***	-9.644***	-12.32***
GCI	-12.08***	-11.25***	-12.36***
GPS	-13.83***	-12.48***	-14.24***
GD	-11.36***	-9.612***	-8.817***
GIS	-12.7***	-12.84***	-12.94***
HAL	-11.32***	-10.05***	-9.793***
HAS	-13.35***	-11.83***	-13.25***

HMA	-11.25***	-10.52***	-11.56***
HES	-12.23***	-8.689***	-11.13***
HPQ	-12.96***	-11.14***	-13.97***
HD	-12.03***	-10.36***	-11.43***
HON	-12.4***	-9.254***	-10.96***
IBM	-12.83***	-10.69***	-13.84***
JCP	-13.34***	-12.09***	-13.55***
JNJ	-10.65***	-11.3***	-11.02***
JCI	-11.47***	-10.2***	-11.1***
KBH	-12.74***	-11.79***	-12.59***
K	-13.36***	-10.97***	-13.18***
KMB	-12.16***	-10.86***	-12.43***
LMT	-11.77***	-11.48***	-10.71***
LOW	-12.96***	-9.609***	-11.29***
MAR	-11.2***	-9.756***	-11.4***
MAS	-12.37***	-9.854***	-11.63***
MCK	-13.22***	-9.963***	-10.36***
MDC	-11.91***	-11.37***	-11.71***
MWV	-13.22***	-10.36***	-9.345***
MDT	-10.86***	-13.09***	-11.57***
MUR	-10.69***	-8.959***	-10.58***
NWL	-12.8***	-10.7***	-11.06***
NEM	-12.39***	-10.24***	-12.75***
NSC	-13.19***	-11.83***	-11.99***
NUE	-12***	-8.548***	-9.58***
OXY	-12.8***	-8.38***	-9.566***
OLN	-12.36***	-11.95***	-12.14***
OMC	-11***	-11.27***	-12.5***
OKE	-11.6***	-7.461***	-8.531***
PKG	-12.1***	-10.82***	-10.94***
PFE	-10.72***	-12.47***	-10.45***
PBI	-12.02***	-12.47***	-12.49***
PG	-10.5***	-9.527***	-10.86***
PHM	-12.54***	-10.71***	-11.77***
RSH	-12.59***	-12.24***	-12.9***
RTN	-12.78***	-11.15***	-11.77***
RSG	-12.45***	-15.83***	-14.89***
RAI	-10.64***	-12.39***	-11.28***
R	-12.94***	-9.921***	-11.89***
RYL	-13.66***	-10.56***	-13.43***
SWY	-13.1***	-12.5***	-13.08***
SRE	-13.61***	-8.695***	-11.36***
SHW	-12.71***	-12.65***	-12.67***
LUV	-12.22***	-11.34***	-11.47***
SPF	-14.47***	-11.04***	-13.96***
SVU	-13.65***	-11.97***	-12.52***
TGT	-12.17***	-7.025***	-11.59***
TSO	-12.82***	-8.517***	-11.45***
TXN	-12.92***	-13.18***	-12.79***
TXT	-10.87***	-8.515***	-10.03***
NYT	-12.85***	-11.1***	-12.82***
TWX	-13.16***	-10.21***	-10.28***
TJX	-12.81***	-10.96***	-11.94***
TSN	-11.62***	-9.282***	-11.33***
UNP	-13.96***	-10.54***	-10.16***

X	-12.93***	-7.049***	-12.27***
UTX	-11.03***	-8.367***	-10.25***
VLO	-13.61***	-8.697***	-10.99***
VZ	-13.12***	-8.71***	-10.54***
VFC	-12.82***	-10.3***	-12.08***
WMT	-11.7***	-10.14***	-11.46***
DIS	-12.25***	-8.833***	-10.65***
WHR	-11.23***	-8.801***	-10.32***
WMB	-12.06***	-7.582***	-8.804***
YUM	-13.1***	-10.32***	-12.68**
Panel B: Panel B: Unit-Root test results of the first-differences of CS and ICS			
Ticker	CS	ICS	One-to-one relation of CS and ICS
MMM	-11.03***	-9.882***	-9.641***
ABT	-12.75***	-13.35***	-13.4***
AA	-12.64***	-6.239***	-11.63***
MO	-9.024***	-10.44***	-9.655***
ABC	-10.46***	-8.779***	-9.943***
APC	-9.623***	-8.542***	-9.571***
APA	-12.92***	-8.444***	-8.27***
T	-13.28***	-9.658***	-12.29***
AVP	-12.35***	-11.77***	-11.88***
BAX	-13.27***	-13.1***	-13.84***
BZH	-14.24***	-11.61***	-14.43***
BMY	-12.38***	-13.59***	-12.86***
CA	-11.2***	-10.89***	-11.37***
CAT	-12.39***	-8.168***	-10.88***
CNP	-9.932***	-8.459***	-9.402***
CTL	-14.34***	-12.45***	-13.18***
CHK	-13.11***	-7.951***	-13.04***
CI	-11.97***	-7.88***	-7.815***
CLX	-12.1***	-12.33***	-12.51***
CMC	-11.44***	-8.22***	-10.62***
CNF	-12.7***	-10.85***	-12.4***
COP	-14.06***	-7.366***	-7.358***
ED	-10.9***	-11.24***	-11.75***
COST	-11.84***	-11.36***	-12***
CSX	-13.48***	-10.73***	-9.915***
CVS	-11.84***	-12.4***	-12.8***
DHR	-11.88***	-11.11***	-11.85***
DRI	-13.99***	-10.98***	-13.71***
DE	-12.3***	-6.496***	-7.77***
DVN	-13.21***	-9.489***	-9.099***
D	-13.25***	-10.29***	-13.11***
DOV	-11.61***	-9.999***	-9.558***
DOW	-10.9***	-10.08***	-10.98***
DHI	-12.85***	-7.326***	-10.41***
DD	-12.88***	-9.449***	-12.21***
LLY	-12.39***	-10.53***	-11.01***
EEP	-9.167***	-10.02***	-10.6***
ETR	-12.08***	-9.874***	-11.77***
EPD	-10.83***	-10.89***	-11.18***
XOM	-11.43***	-10.07***	-11.89***
FE	-12.99***	-10.98***	-11.77***
F	-13.1***	-12.69***	-13.16***
GCI	-12.13***	-10.55***	-11.98***

GPS	-13.7***	-12.4***	-13.83***
GD	-11.46***	-10.2***	-9.479***
GIS	-12.72***	-12.75***	-13.08***
HAL	-11.18***	-9.594***	-9.271***
HAS	-13.32***	-12.46***	-13.04***
HMA	-11.13***	-12.15***	-12.17***
HES	-12.18***	-8.045***	-9.217***
HPQ	-13.01***	-10.75***	-13.44***
HD	-12.17***	-11.01***	-11.82***
HON	-12.44***	-9.011***	-9.924***
IBM	-12.75***	-10.77***	-13.67***
JCP	-13.17***	-12.31***	-13.13***
JNJ	-10.75***	-11.26***	-11.56***
JCI	-11.43***	-9.762***	-11.83***
KBH	-12.72***	-12.27***	-12.85***
K	-13.35***	-11***	-13.26***
KMB	-12.21***	-10.35***	-12.47***
LMT	-11.71***	-11.72***	-11.27***
LOW	-12.98***	-10.38***	-11.93***
MAR	-11.21***	-10.46***	-11.42***
MAS	-12.41***	-10.28***	-12.48***
MCK	-13.08***	-11.52***	-11.43***
MDC	-11.91***	-9.228***	-10.13***
MWV	-13.42***	-10.17***	-10.24***
MDT	-11.1***	-12.87***	-11.87***
MUR	-10.72***	-9.007***	-10.5***
NWL	-12.75***	-11.23***	-11.67***
NEM	-12.41***	-9.457***	-12.16***
NSC	-13.31***	-11.38***	-11.12***
NUE	-11.82***	-8.54***	-9.016***
OXY	-13.12***	-8.217***	-8.714***
OLN	-12.33***	-11.09***	-11.38***
OMC	-10.99***	-11.16***	-12.52***
OKE	-11.62***	-7.678***	-8.127***
PKG	-12.04***	-10.38***	-10.69***
PFE	-10.85***	-12.61***	-11.11***
PBI	-11.97***	-12.53***	-12.4***
PG	-10.56***	-9.278***	-10.86***
PHM	-12.53***	-8.789***	-10.92***
RSH	-12.37***	-11.76***	-12.76***
RTN	-12.71***	-11.42***	-11.71***
RSG	-12.22***	-16.62***	-15.46***
RAI	-10.62***	-13.13***	-11.77***
R	-13.04***	-9.739***	-11.08***
RYL	-13.68***	-10.92***	-13.72***
SWY	-13.08***	-12.89***	-13.78***
SRE	-13.64***	-8.595***	-9.944***
SHW	-12.79***	-13.2***	-12.76***
LUV	-12.24***	-11.66***	-11.9***
SPF	-14.36***	-11.83***	-14.39***
SVU	-13.57***	-13.9***	-14.23***
TGT	-12.26***	-7.383***	-11.23***
TSO	-12.82***	-9.006***	-11.87***
TXN	-12.79***	-13.07***	-12.68***
TXT	-11.72***	-8.588***	-10.92***

NYT	-12.63***	-11.16***	-12.89***
TWX	-12.74***	-11.7***	-11.85***
TJX	-12.8***	-10.2***	-12.2***
TSN	-11.63***	-8.179***	-10.77***
UNP	-13.9***	-9.591***	-9.185***
X	-12.87***	-6.879***	-13.06***
UTX	-10.99***	-9.959***	-11.11***
VLO	-13.74***	-7.579***	-8.997***
VZ	-13.11***	-11.42***	-11.77***
VFC	-12.79***	-11.34***	-12.04***
WMT	-11.64***	-11.46***	-11.63***
DIS	-12.17***	-8.773***	-10.22***
WHR	-11.11***	-9.544***	-10.27***
WMB	-12.13***	-6.368***	-7.61***
YUM	-13.16***	-10.52***	-12.18***

Notes: This table reports the results of the ADF Unit-Root Tests on the first-difference of LCS (CS) and the first-difference of LICS (ICS). The stock ticker of each reference entity in our sample is in the first column. The critical value is -2.863 at 5% and -3.437 at 1% level of significance, respectively. ** and *** indicate the test statistic to be significant at 5% and 1%, respectively. For the test of one-to-one cointegration, as Lien and Shrestha (2014) do, the difference between LCS (CS) and LICS (ICS) is calculated. If the difference is non-stationary, then the one-to-one cointegrating relationship can be rejected. The results show that the first difference of the difference between LCS (CS) and LICS (ICS) is stationary in almost all the cases.

Chapter 3: 'Too-Interconnected-To-Fail' Financial Institutions: Evidence from the Transmission of Credit Risk across the G-SIFIs

3.1 Introduction

The collapses of major financial companies and the subsequent meltdowns of financial markets around the world in late 2008 have highlighted the need to address the systemic risk posed by large international financial institutions that are considered to be 'too-interconnected-to-fail'. To directly address the risks inherent in these large, complex, interconnected firms, the Financial Stability Board (FSB) has formally identified and released two lists of financial institutions that are deemed to be systemically important to the global economy (G-SIFIs) in the sense that failure of one of them could pose negative externalities to the whole financial system and trigger a global financial crisis, that is, global systemically important banks (G-SIBs) and global systemically important insurers (G-SIIs). New regulatory standards and extra loss absorbency requirements have since been imposed on these G-SIFIs to ensure that they are not only less likely to fail, but also can do so without adverse consequences.[12]

Since the publication of these long-awaited lists of G-SIFIs, measuring and monitoring the systemic risk and financial connectedness of these special groups of financial firms have remained a top priority in academic research and policymaking agendas. There is general agreement that, whilst the dependencies and interconnections among the large financial firms may not always be detrimental, it is important to assess and monitor the risks posed to the broader financial system by individual financial institutions and to

[12] See, for instance, the FSB's (2011) Policy Measures to Address Systematically Important Financial Institutions, which defines SIFIs, at both the global level (G-SIFIs) and the domestic level (D-SIFIs), as '*financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economy activity*'.

understand when the interconnectedness is so extreme that it can severely disrupt the international financial system. Billio et al. (2012) define systemic risk as the risk that during the periods of financial distress, illiquidity, insolvency, and capital losses of one financial institution would quickly propagate to the other closely connected financial firms through business activities. They argue that an effective systemic risk measure should capture the degree of interconnectivity of financial stakeholders and of the default probability, along with other factors, such as size, substitutability, complexity, and global (cross-jurisdictional) activity. Zhang et al. (2015) also agree that the degree of interconnection is an important possible driver of systemic risk since it can magnify externalities of financial distress via contagion.

The growing literature on systemic risk in the G-SIFIs has focused primarily on a range of methodological issues relating to a) the measurement and identification of potential G-SIFIs (e.g., Yang and Zhou, 2013; Banulescu and Dumitrescu, 2015), b) testing stock market reactions to the publication of the lists of G-SIFIs (e.g., Abreu and Gulamhussen, 2013; Bongini et al., 2015), and c) detecting stock return and volatility transmissions across the G-SIFIs (e.g., Elyasiani et al., 2015). Relatively little is known about credit default risk transmission across the systemically important banks and insurers. This is somewhat surprising given the growing concern that '*their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries* (FSB, 2010)'. Although structural credit risk models suggest that firms' default likelihood can be derived from the stock market data and the empirical results of Chapter 2 support the general dominating role of the stock market in credit risk discovery for non-financial firms, a strand of literature argues that CDS spread could be a better and direct default risk proxy for financial institution. For instance, Chiaramonte and Casu (2013) claim that CDS spread provides a simple and straightforward indicator of market judgement of a financial institution's default risk, especially during the crisis times. Rodríguez-Moreno and Peña (2013) suggest that as CDS spread contains direct information on probability of default, it is better than stock price in investigating financial firms' systemic risk. Acharya et al. (2017) provide two reasons why CDS spread might be better than stock data in studying systemic risk posed by financial institutions. On the one hand, CDS spread estimates the losses of the market value of a financial institution's assets, not just its equity. On the other hand, as financial firm's debt may be implicitly or explicitly guaranteed by government creditworthiness, CDS spread is better in terms of reflecting the underlying value of financial firm's debt. Thus, this chapter is motivated to employ the default risk information provided by CDS spread to examine default risk connectedness across large financial institutions.

Using the information content in bank and insurer CDS spreads, Billio et al. (2013) and Yang and Zhou (2013) present the first attempt in examining credit risk connectedness among financial firms during the global financial crisis. However, these studies have several shortcomings rendering the validity of empirical results. For instance, Billio et al. (2013) focus only on the pairwise connectivity of credit risk of sovereigns, banks, and insurance firms. Yang and Zhou (2013) do not measure the dynamics of credit risk transmission across financial institutions. This chapter employs Diebold and Yilmaz's (2015a) VECM-based connectedness measures. Complementing the existing systemic risk measures, their approach offers a wider range of directed and weighted systemic risk indicators, from firm-level pairwise directional connectedness measures to system-wide aggregate connectedness measures. Compared with Diebold and Yilmaz's (2014) VAR-based connectedness measures, VECM model allows for possible cointegration relations. Given the level of interbank lending activities among global banks and that of similar investment holdings of international financial institutions, it is not surprising that their default risk, as measured by CDS spreads, may share long-term cointegrating relationships. While several studies have examined factors affecting financial firms' systemic risk and/or risk spillovers, they either apply systemic risk measures calculated by using stock data or omit several possible drivers. Thus, this chapter suggests several possible driving forces of negative credit risk externalities of individual G-SIFIs, such as interbank loans and unconventional banking activity, regulatory capital ratios, and additional loss absorbency bucket allocations of G-SIBs (published by the FSB). In sum, the objectives of this chapter are to investigate the transmission mechanism of default risk among G-SIFIs (identifying which bank or insurer is the major transmitter of credit risk shock) and to examine the factors underlying each G-SIFI's systemic importance. The following research questions are addressed.

a) How do credit risk shocks transmit across the identified G-SIFIs? In particular, which bank or insurer transfers the most credit risk shocks to the rest of the G-SIFIs?
b) What factors explain the systemic importance of individual G-SIFIs in the credit risk transmission mechanism?

The major findings can be summarised as follows. Over the entire sample period of the years 2006–2014, the total credit risk connectedness among G-SIFIs is generally high. It increases substantially from less than 75% in mid-2006 to 95% in mid-2008, and it has remained above 90% since then. The periods of unusually high credit risk spillovers, as quantified by a 'scored' credit risk connectedness measure, occurred during the periods of widely publicised financial episodes. Compared with the G-SIFIs from the EU and those from Asia, the U.S.-based G-SIFIs are generally major credit risk senders. In comparison with insurance firms, banks are more systemically important in the credit risk transmission. Finally, a bank is more likely to be net credit risk transmitter when it has more interbank loans, more non-interest income (especially trading book income), and lower Tier 1 leverage ratio, and when it is distributed to a higher additional loss absorbency bucket. An insurer plays a more crucial role in sending credit risk shocks if it has more non-traditional non-insurance business, larger size, and more global sales.

This chapter contributes to the existing literature in a number of aspects. First, this study extends the existing understanding of credit risk spillovers across financial institutions by focusing on a special group of financial firms, that is, the G-SIFIs. Second, different from Diebold and Yilmaz (2015a), this chapter documents that the empirical findings obtained from VECM model and VAR model share qualitatively similar patterns. Third, this chapter proposes a new 'too-interconnected-to-fail' ranking to identify the major credit risk providers and receivers in this special group of financial firms. This ranking is complementary to the existing official list published by the FSB in capturing the multiple facets of systemic risk. Unlike the official list which is based on balance-sheet data, our ranking is derived directly from CDS market data and should reflect, at least in part, market participants' expectations of each G-SIFI's systemic importance in credit risk spillovers. Regulators may combine these two lists to construct a 'composite' systemic risk ranking that considers various sources of information, including market and accounting data. Finally, this chapter offers further evidence of the drivers of credit risk spillovers of G-SIFIs, which helps regulators design more effective policies.

The rest of this chapter is organized as follows. Section 3.2 reviews relevant literature and develops hypotheses. Section 3.3 describes Diebold and Yilmaz's (2015a) VECM-based connectedness measures and presents the framework we use to construct the 'too-interconnected-to-fail' ranking and to examine the drivers of G-SIFI's role in global credit risk transmission. Section 3.4 presents the data and the preliminary analysis. The main empirical findings are reported in Section 3.5. Section 3.6 is conclusion.

3.2 Related Literature and Hypothesis Development

3.2.1 Market-Based Systemic Risk Measures

To support regulators and supervisors in measuring systemic risk, extensive research has put forward numerous metrics which rely only on public financial information and reflect market expectations.[13] Table 3.1 provides a brief summary of the major market-based systemic risk measures.[14] Some of these metrics concentrate on the contribution of one firm's default to the system-wide distress, e.g., Adrian and Brunnermeier's (2016) Conditional VaR (CoVaR). Several indicators focus on the degree of vulnerability of a financial company in the case of a systemic event, e.g., Acharya et al.'s (2017) marginal expected shortfall (MES) and Brownlees and Engle's (2017) SRISK. Some others focus on the interconnections across financial institutions in the system, e.g., Billio et al.'s (2012) connectedness measures.

Diebold and Yilmaz's (2014) measures concentrate on the connectivity among financial firms. They argue that their framework unifies several systemic risk metrics. The 'From' statistic measures individual firms' exposures to systemic shocks, which is analogous to MES; the 'To' statistic quantifies individual firms' contributions to systemic events, which is analogous to $\Delta CoVaR$; the 'Total' statistic aggregates firm-specific systemic risk across all the institutions in the financial system, which is analogous to aggregated SRISK. Several extensions of Diebold and Yilmaz's (2014) connectedness measures

[13] BCBS (2013) acknowledges that "No approach will perfectly measure global systemic importance across all banks." The usefulness and potential model risks of market-based systemic risk measures are criticised by Zhang et al. (2015) and Danielsson et al. (2016a), respectively. Nonetheless, compared with the indicator-based systemic risk measures currently used by supervisory authorities, the market-based indicators can provide timely assessments of financial firms' systemic risk and convey, at least in part, market participants' expectations. Thus, although the market-based metrics have several flaws, it is still important for regulators to appropriately adopt them as 'cross-check' tools (Weistroffer et al., 2011).

[14] More comprehensive surveys of the main systemic risk measures can be found in Bisias et al. (2012), Nucera et al. (2016), Giglio et al. (2016), and Benoit et al. (2016).

have been proposed in the recent literature. For example, Alter and Beyer (2014) use generalised impulse response functions in VAR model with exogenous factors to devise a contagion index that can quantify ‘excess spillovers’ among the examined variables. To incorporate any long-term equilibrium relationships shared by dependent variables, Diebold and Yilmaz (2015a) construct connectedness measures based on VECM model. In VAR and VECM models, Barunik and Krehlik (2015) use spectral representation of variance decomposition of forecast errors to gauge frequency-dependent connectedness, which considers shocks at different frequencies with different strength. Based on the BEKK-GARCH model, Fengler and Herwartz (2015) propose a time-varying variance spillover index that exploits the information content of variance-covariance dynamics.

3.2.2 Connectedness of Financial Institutions

Table 3.2 briefly summarises the existing empirical evidence about interconnectedness among financial firms. As shown, Billio et al. (2012) document that in the past decade, stock return connectedness across hedge funds, banks, broker/dealers, and insurers has increased to a higher level via a complex and dynamic network of causal relationships. Elyasiani et al. (2015) find that the U.S. financial institutions are major stock return and volatility transmitters to their peers in other countries, such as Japanese financial firms. Regarding the relationships between banks and insurers, Harrington (2009) claims that compared with banks, insurance companies seem to be less risky because they have no deposit runs and have more capital holdings. Billio et al. (2012) and Chen et al. (2014) present that although bidirectional spillovers across banking and insurance sectors can be observed, banks play as the primary shock providers.

Most of the existing literature uses stock market data, with only a few exceptions, such as Billio et al. (2013) and Yang and Zhou (2013) who employ information from CDS market. However, it has been suggested that CDS spread is a better and straightforward default risk proxy for financial institution. For example, Chiaramonte and Casu (2013), Rodríguez-Moreno and Peña (2013), and Acharya et al. (2017) agree that because CDS spread contains direct information on market expectation of default probability of one financial firm, it is better than stock price in examining financial firms' systemic risk. While Billio et al. (2013) and Yang and Zhou (2013) use CDS data, their studies have shortcomings. The PCA-based connectedness measures employed by Billio et al. (2013) indicate only the pairwise linear dependency, depend on arbitrary significance levels, and fail to track the size of non-zero coefficients (Diebold and Yilmaz, 2014). Yang and Zhou (2013) provide only a static view about credit risk linkages across financial institutions. We complement these previous studies by using CDS data and Diebold and Yilmaz's (2015a) connectedness metrics which yield multilevel, directional, dynamic, and daily credit risk interdependence across financial firms.

3.2.3 Determinants of Connectedness of Financial Institutions

In the growing literature, the role of leverage, size, corporate governance, deposit insurance policy, competition, and domestic regulatory environment in affecting banks' systemic risk or risk spillovers has been widely studied. Allen et al. (2012a) and Yang and Zhou (2013) find that financial institutions which rely intensively on short-term financing generate more systemic risk. Yang and Zhou (2013) discover that size has negative but insignificant impact on one financial firm' spillover score (SS)[15], while Bostandzic et al. (2014) and Laeven et al. (2016) present that size is one of the primary

[15] Based on the identified contemporaneous causal linkages among financial firms, Yang and Zhou (2013) assign a spillover score (SS) to each firm. SS can measure the extent of risk spillover from one firm to the rest of firms in the financial system. SS=3 indicates a strong risk sender and a weak risk receiver; SS=2 indicates a strong risk transmitter and a strong risk receiver; SS=1 indicates a weak risk sender and a strong risk receiver; SS=0 indicates a weak risk provider and a weak risk receiver. Elyasiani et al. (2015) also use SS, but they use stock data rather than CDS data.

determinants of banks' systemic risk. Iqbal et al. (2015) suggest that better corporate governance amplifies rather than alleviates financial firms' systemic relevance, while Yang and Zhou (2013) cannot find a significant impact of corporate governance on one financial firm's SS. Anginer et al. (2014a) show that although explicit deposit insurance and full deposit insurance coverage reduce banks' exposures to systemic risk during the crisis times, their overall effects over the full sample period are detrimental. Bostandzic et al. (2014) report that the explicit deposit insurance policy which requires banks to contribute more financial resources increases both exposures and contributions of banks to systemic risk. In addition, Anginer et al. (2014b) document that greater competition benefits the stability of the banking system. They also find that the countries with strong regulation, less government ownership of banks, and less competition restrictions have lower systemic risk in their banking system.

Different from the above mentioned literature, this chapter examines the impact of four bank-specific characteristics, i.e., interbank loans, unconventional bank activity, capital adequacy, and extra loss absorbency requirement, on G-SIBs' credit risk transmissions. Systemic risk can be defined as the risk that the distress of one financial firm propagates to other financial institutions through their business links (Furfine, 2003). The financial linkages between banks consist of, but are not limited to, interbank loans, payment systems, and derivatives positions (Krause and Giansante, 2012). Intuitively, as argued by Rochet and Tirole (1996), while interbank lending may incentivise peer monitoring, it may increase systemic risk since it results in a higher interconnection between banks. Thus, a G-SIB with a higher interbank exposure is expected to be more systemically important because it is more likely to transfer credit risk shocks to other G-SIBs through its interbank business activities. Proposing and applying the participation approach (PA) and generalised contribution approach (GCA) based on Shapley values, Drehmann and

Tarashev (2011, 2013) present that banks with greater interbank borrowing/lending are more systemically relevant. Hence, we develop the following hypothesis.

Hypothesis 1(a): The more interbank loans a G-SIB has, the greater role it would play in credit risk transmission.

Motivated by deregulation initiatives and better performance, banks prefer to engage in risky non-banking activities (DeYoung and Torna, 2013). While untraditional banking business may provide banks diversification opportunities (Saunders and Walter, 1994), the risk embedded in those unconventional banking activities may be more appropriate for other financial intermediaries such as hedge funds (Billio et al., 2012). Hence, the inference to be drawn is that a bank heavily depending on non-interest income would be more risky and systemically relevant. In line with the empirical findings of DeYoung and Roland (2001) and Stiroh (2004, 2006), DeJonghe (2010) presents that non-interest income, e.g., commission and fee income, trading income, and other operating income, increases European banks' tail betas. In terms of the U.S. commercial banks, DeYoung and Torna (2013) find that asset-based non-banking activities, e.g., investment banking, venture capital, and asset securitization, are positively related to the distressed bank's default probability. In contrast to Bostandzic et al. (2014), Brunnermeier et al. (2012) find that banks with more non-interest income have higher systemic risk contributions measured by ΔCoVaR and systemic expected shortfall (SES). Accordingly, we develop the following hypothesis.

Hypothesis 1(b): The more non-interest income a G-SIB has, the greater role it would play in credit risk transmission.

Since 1988, the capital adequacy of financial firms has always been the key interest of regulators and supervisors. However, the defaults of large financial institutions during the recent financial crisis undoubtedly questioned the effectiveness of the existing capital regulation framework (Demirgüç-Kunt et al., 2013). In July 2010, the Basel Committee proposed a Tier 1 leverage ratio requirement which is based on gross non-risk-adjusted assets. This capital surcharge aims to supplement Tier 1 and Tier 2 capital requirements that are based on risk-weighted assets and address the criticism associated with arbitrary risk exposure computations under the Basel rules (Fender and Lewrick, 2015). Intuitively, since better-capitalised banks have more capital to withstand adverse shocks and absorb unexpected losses (e.g., VanHoose, 2007), they would be less likely to default and contribute more systemic risk. Bostandzic et al. (2014) show that banks with more Tier 1 capital have less exposures and contributions to systemic risk, which is supported by the findings of Laeven et al. (2016). Although it is unknown whether Tier 1 leverage ratio and leverage ratio (divide the sum of Tier 1 and Tier 2 capital by total assets) could influence banks' systemic importance, Demirgüç-Kunt et al. (2013) discover that large banks' stock returns are more sensitive to Tier 1 leverage ratio and leverage ratio than to Tier 1 capital ratio. Using four proxies of capital adequacy, that is, Tier 1 capital ratio, capital adequacy ratio, Tier 1 leverage ratio, and leverage ratio, this chapter tests the following hypothesis.

Hypothesis 1(c): The lower capital adequacy a G-SIB has, the greater role it would play in credit risk transmission.

Since November 2012, based on the assessment scores obtained by using the BCBS methodology, the FSB has allocated the yearly designated G-SIBs to five buckets. Each bucket represents a Tier 1 common equity capital ratio (CET1) level that G-SIBs must hold in addition to the Basel III minimum CET1 requirement.[16] The higher bucket a G-SIB is assigned, the more systemically relevant it is. The requirements are phased in from January 2016, with full implementation by January 2019 (FSB, 2013).[17] Being identified as a G-SIB is more likely to be negative news because of extra regulatory costs and supervisory scrutiny (Bongini et al., 2015; Danielsson et al., 2016b). Higher regulatory burden may even incentivise the G-SIBs to get involved in riskier financial innovations or investments to circumvent the stringent regulations and to survive in the fierce competition with their non-systemically important rivals, which may in turn threaten the global financial stability (Slovik, 2012).

Hypothesis 1(d): The higher additional loss absorbency bucket a G-SIB is distributed, the greater role it would play in credit risk transmission.

Regarding insurers, Weiß and Mühlnickel (2014) study the impact of size, leverage, and other factors identified by the International Association of Insurance Supervisors (IAIS) (2013) on the systemic risk exposures and contributions of the U.S. insurers from 2007 to 2008. Bierth et al. (2015) extend Weiß and Mühlnickel's (2014) work by using an international sample and a longer sample period. Both studies employ MES, ΔCoVaR, and SRISK to measure systemic risk. Weiß and Mühlnickel (2014) find that insurers which have higher exposures to systemic risk are larger, relying more heavily on non-core insurance business, and more successful in investment activities. However, insurers' contributions to systemic risk are driven only by firm size. Bierth et al. (2015)

[16] Bucket 1: extra 1% CET1; bucket 2: extra 1.5% CET1; bucket 3: extra 2% CET1; bucket 4: extra 2.5% CET1; bucket 5: extra 3.5% CET1. Bucket 5 is used as an incentive to curb banks to become more systemically important. If Bucket 5 is populated, the sixth bucket will be added for the same purpose.

[17] According to the FSB (2013), the extra CET1 requirements for the G-SIBs designated in the annual update each November will apply to them as from January fourteen months later. It means that, for example, the G-SIBs identified in November 2014 need to hold the required additional CET1 from January 2016 onwards. The G-SIBs identified in November 2015 need to hold the required extra CET1 from January 2017 onwards.

document that insurance firms' systemic risk is affected by various factors including interconnectedness, size, and leverage, while the magnitudes and significances of the effects of driving forces vary with different systemic risk measures, insurance lines (life or non-life insurers), and geographic regions.

Based on the findings of the above mentioned studies, this chapter focuses on two main drivers: non-traditional and non-insurance (NTNI) activity and size. Engaging in more NTNI activities, e.g., CDS underwriting activities, has been considered as one of the primary reasons causing the distress of AIG (Cummins and Weiss, 2014). Thus, G-SIIs with more NTNI business are expected to generate more systemic risk. This conjecture is empirically supported by the findings of Bierth et al. (2015). In terms of firm size, insurance businesses are based on the law of large numbers, that is, as the number of risks in a portfolio increases, the risk of the portfolio declines (Weiß and Mühlnickel, 2014). However, Acharya et al. (2009) argue that larger insurers, such as AIG, are more likely to be 'too-interconnected-to-fail', so they become more systemically important. Weiß and Mühlnickel (2014) and Irresberger et al. (2016) empirically confirm that size is positively related to insurers' systemic risk. Thus, we test the following hypotheses.

Hypothesis 2(a): The more NTNI business a G-SII has, the greater role it would play in credit risk transmission.

Hypothesis 2(b): The larger size a G-SII has, the more systemically important it would be in credit risk transmission.

3.3 Methodology

3.3.1 VECM-based Connectedness Measures

Consider the following model for CDS spreads of G-SIFIs,

$$\Delta X_t = -\Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + U_t, U_t \sim N(0, \Sigma) \quad (3.1)$$

where ΔX_t is a $N \times 1$ vector of first log-difference of CDS spreads. Lag k is selected based on Schwarz Information Criterion (SBC). Γ_i are $N \times N$ coefficient matrices, for $i = 1, 2, \dots, k-1$. Σ is assumed to be constant for all t.[18] Suppose there is a $N \times r$ matrix β so that the $r \times 1$ vector $z_t = \beta' X_t$ is stationary, where $1 \leq r < N$. The cointegration relations can be expressed as: $\Pi = \alpha\beta'$, where α is a $N \times r$ matrix, with rank $(\Pi) = r$. Since ΔX_t are stationary, ΔX_t can be rewritten as the vector moving average representation:

$$\Delta X_t = \sum_{i=0}^{\infty} A_i U_{t-i} \quad (3.2)$$

where A_i are $N \times N$ coefficient matrices, for $i = 0, 1, 2, \dots$ To identify shocks, the generalised variance decomposition (GVD) proposed by Koop et al. (1996) and Pesaran and Shin (1998) (KPPS) is employed. GVD is ordering invariant and considers shocks by using historically observed distribution of the errors. Denote the KPPS H-step-ahead GVD as $\theta_{ij}^{g}(H)$, for $H = 1, 2, \dots$, such that:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)} \quad (3.3)$$

where σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is a vector with one at the ith element and zeros otherwise. The sum of the elements in each

[18] It can be noted that the variance-covariance matrix of U_t, Σ, could also be time-varying, that is, VECM-GARCH model. However, given the complexity and computation burden in the estimation of VECM-GARCH model, the empirical applications of the modified connectedness measures may be significantly limited (See, e.g., Fengler and Herwartz, 2015). As the purpose of this chapter is to examine the transmission of credit default risk of a relatively large system of G-SIFIs across the U.S., the EU, and Asia, Σ is assumed to be constant.

row of the variance decomposition table is not necessarily equal to 1: $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Thus, normalise each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3.4}$$

$\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. **Total** connectedness measure is defined as:

$$C^{g}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3.5}$$

To identify the origin of connectedness, **directional** connectedness measure is defined. Directional connectedness obtained by market i from all other markets j and directional connectedness transmitted by market i to all other markets j are:

$$C_{i.}^{g}(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3.6}$$

$$C_{.i}^{g}(\mathrm{H}) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{3.7}$$

Net connectedness measure and net pairwise connectedness measure are computed as:

$$C_{i}^{g}(H) = C_{.i}^{g}(H) - C_{i.}^{g}(H) \tag{3.8}$$

$$C_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) \times 100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) \times 100 \tag{3.9}$$

As a benchmark, we also use VAR-based connectedness metrics in empirical analyses.

3.3.2 Ranking of 'Too-Interconnected-To-Fail' Financial Firms

Using rolling-window estimation method, this chapter calculates a variety of dynamic credit risk connectedness measures for G-SIFIs. Then, we compute the yearly average net directional credit risk connectedness of individual G-SIFIs and rank the values from the lowest to the highest. Next, we assign a score, ranging from 1 to N, to each G-SIFI. N is the total number of G-SIFIs in the sample. The higher (lower) the score, the more (less) important the role of G-SIFI is in the global credit risk transmission. This ranking is updated yearly and is referred to as 'too-interconnected-to-fail' ranking.[19] It is noted that, unlike the FSB list which is based on balance-sheet data, this 'too-interconnected-to-fail' ranking is derived directly from CDS market data and can reveal investors' expectations about individual G-SIFI's systemic importance in credit risk transmission.

3.3.3 Determinants of the 'Too-Interconnected-To-Fail' Ranking

This study also examines the determinants of the strength of credit risk spillovers across G-SIFIs. In particular, the following regression (similar to that of Yang and Zhou, 2013; Elyasiani et al., 2015) is used to examine the driving forces of credit risk transmission:[20]

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \tag{3.10}$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t. γ and ξ are the vectors of coefficients. To alleviate the concern that dependent variable and explanatory variables could be determined simultaneously (Bierth et al., 2015), all the independent variables are lagged by one period. Given that banks and insurers have distinct business models, it is appropriate to adopt a diverse set of explanatory and control variables for G-SIBs and G-SIIs estimations so that the drivers of the strength of credit risk spillovers

[19] Indeed, one can construct such a ranking using data at various frequencies, ranging from daily to yearly. We choose to derive a yearly ranking because this can facilitate the ensuing analysis on the determinants of credit risk spillovers. The data of several main drivers are firm-specific accounting data and are available only at the yearly frequency.

[20] To address the concern that our dependent variable is non-continuous, we consider several alternative estimation frameworks to check the sensitivity of results. Both the ordinal probit and logit models are used to investigate this issue and the results reported in Table 3.17 confirm that the main empirical findings remain qualitatively the same as those shown in Table 3.12 and 3.13.

among banks and insurers can be tested separately. For G-SIBs, $W_{i,t-1}$ is a vector of the proxies of interbank loans, non-interest income, regulatory capital ratio, and extra loss absorbency requirement. $Z_{i,t-1}$ is a vector of control variables, which contains the proxies of international business, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition index of the region in which a G-SIB is located. For G-SIIs, $W_{i,t-1}$ is a vector of the proxies of non-traditional non-insurance (NTNI) activity and size. Again, $Z_{i,t-1}$ is a vector of control variables, which includes the proxies of international business, G-SII designation, corporate governance, insurance portfolio quality, leverage, investment activity, operating efficiency, management effectiveness, GDP growth rate, and financial condition index of the region in which a G-SII is located.

3.4 Data

3.4.1 Data Sources

Since 2010, the FSB has released 5 lists of G-SIBs and 3 lists of G-SIIs. All G-SIFIs that have been included in these lists are considered in this chapter. The sample period is from 02/01/2006 to 31/12/2014. Daily data of 5-year single-name CDS contracts written on senior unsecured debt are obtained from DataStream. The restructuring type depends, however, on regional preference (as specified by Thomson Reuters). For the Asian CDS, it is CR (fully restructured); for the European CDS, it is MM (Modified Modified restructuring); and for the U.S. CDS, it is XR (no restructuring). In the final sample, there are a total of 32 G-SIFIs, consisting of 23 G-SIBs and 9 G-SIIs. Following Yang and Zhou (2013), two-day rolling averages of CDS spreads are used to smooth out sharp daily movements and irregular trading (Eichengreen et al., 2012) and to control for the asynchronous trading issue (Forbes and Rigobon, 2002). The definitions and data sources for the key variables used in the analysis of determinants of credit risk spillovers are reported in Table 3.3 and 3.4, respectively. All the yearly accounting data are measured in U.S. dollars to mitigate any possible bias stemming from currency risk (e.g., Bierth et al., 2015).

3.4.2 Preliminary Data Analysis

Summary statistics on CDS spreads of 32 G-SIFIs are reported in Table 3.5. The table shows that average spreads during the sample period vary substantially across G-SIFIs, from 51.384 basis points (bps) for Mitsubishi UFJ FG to 307.357 bps for AIG. The standard deviations of CDS spreads are generally close to the means and become larger in the case of three G-SIIs: Prudential, Prudential Financial, and AIG. The large range in CDS spreads of several financial firms reveals considerable variations in their default risk over the sample period, e.g., Prudential Financial (10.2 to 1,314.1 bps), AIG (8 to 4,639.0 bps), and Morgan Stanley (17.25 to 1,197.01 bps). Their default risk became extremely high during the 2007–2008 global financial crisis. The test statistics of the Augmented Dickey-Fuller (ADF) unit-root test and Johansen cointegration test are presented in Table 3.6 and 3.7, respectively. All the CDS spreads are non-stationary at log-levels and stationary at first log-differences.[21] Based on the results of trace test, we find five long-run equilibrium relations among CDS spreads of 32 G-SIFIs.

Table 3.8 reports summary statistics of the determinants of the 'too-interconnected-to-fail' ranking of G-SIFIs, and we briefly discuss the statistics data for the drivers of main interest. Panel A of the table reveals that the mean of the log of interbank loans of the

[21] Pedrosa and Roll (1998) find that credit spreads are I (1) process. They suggest that the unit-root behaviour of credit spreads is driven by risk-free interest rate and investors' view of volatility and asset values. Since CDS spread is a subset of credit spread, it is reasonable to expect that CDS spread is non-stationary. The non-stationary nature of CDS spread has been confirmed by previous studies related to the determinants of CDS spread, e.g., Davies (2008) and Galil et al. (2014).

G-SIBs is 7.69. On average, the non-banking income accounts for 64% of the total interest income, and a larger part of it is generated by other non-banking business rather than trading activities. In terms of the four proxies of capital adequacy, the average Tier 1 capital ratio (capital adequacy ratio) is 10.96 (14.19) per cent, as compared to 4.25 (5.82) per cent for Tier 1 leverage ratio (leverage ratio). The large ranges in the four capital adequacy proxies suggest considerable variations in regulatory capital held by the G-SIBs over the sample period. For example, Tier 1 capital ratio ranges from 6.44 to 21.40 per cent. Panel B of the table shows that for the G-SIIs, the ratio of the total liability to total insurance reserves, a proxy for non-core activities (NTNI) of insurers, ranges from 1.07 to 3.06, with a mean ratio of 1.79. It implies that on average the amount of non-policyholder liabilities accounts for roughly 80% of that of insurance liabilities. Other income, another proxy for NTNI, has a mean of 163,000 US$ with a large standard deviation of 21.23. As expected, in contrast to the G-SIBs, the G-SIIs have smaller firm sizes (e.g., Geneva Association, 2010). As shown in Table 3.9, the absolute values of pairwise correlations between derivers are generally smaller than 0.5, implying no multicollinearity in the regression analyses.

3.5 Empirical Results

3.5.1 Static Credit Risk Connectedness

Static credit risk connectedness tables are presented in Table 3.10. After accounting for the long-run cointegration relations shared by CDS spreads of G-SIFIs, the total credit risk connectedness generated by using the VECM model (88.2%) is slightly higher than that obtained by using the VAR model (86.3%).[22] According to the pairwise directional connectedness measures, G-SIIs (the first 9 firms) and G-SIBs (from the 10th to the

[22] Since the empirical results yielded by VECM and VAR models are qualitatively similar, all the discussions in Section 3.5 are based on the results generated by VECM model.

32nd firm) do not operate independently and are linked closely with each other probably due to derivatives positions and similar investment holdings. This result is in line with the finding of Chen et al. (2014). In particular, the G-SIFIs from the U.S. and the EU have higher pairwise directional credit risk dependency with each other and contribute more total directional credit risk connectedness to the other G-SIFIs. However, the G-SIBs from Japan and China appear to be rather isolated from all their peers. One possible reason is that these Asian banks are relatively highly regulated by domestic regulators; therefore, they have weaker interactions with other international banks. Elyasiani et al. (2015) draw similar conclusions when they investigate stock return and volatility spillovers across multinational financial institutions.

3.5.2 Dynamic Credit Risk Connectedness

3.5.2.1 Total Credit Risk Connectedness of G-SIFIs

Dynamic credit risk connectedness is obtained by using 5-day forecast horizon and 100-day rolling window.[23] The total credit risk connectedness of G-SIFIs is plotted in Figure 3.1. Several important observations can be drawn. First, after mid-2006, system-wide credit risk connectedness of G-SIFIs increases dramatically from 75% to 95% and then fluctuates around 92% until the end of 2014. This finding is somewhat different from that of Diebold and Yilmaz (2015b), who show that after September 2012, the total stock price volatility connectedness among the 28 financial institutions in the EU and the U.S. drops to roughly 75% and does not reach 80% again until 2014. These different results may be attributed to two possible reasons. One is that the 28 financial firms analysed in Diebold and Yilmaz (2015b) are not all G-SIFIs and, thus, they do not fully represent the globally important banks and insurers. Besides, their stock price volatility

[23] We check the sensitivity of the results to different forecast horizons and rolling widow sizes in Section 3.5.5.

connectedness indicator alone may fall short in capturing the multiple facets of risk transmission among these large, complex, internationally active financial institutions.

The existing studies suggest that the dependency among financial institutions may not always be detrimental, e.g., Rochet and Tirole (1996).[24] However, it is important and informative to further investigate the period in which the interconnectedness is so 'extreme' that can severely disrupt the international financial system (Yellen, 2013). In particular, we follow Chau and Deesomsak (2014) to construct various categories of credit risk connectedness (CRC) severity in order to monitor the severity of CRC among G-SIFIs. First, a measure of how many standard deviations the current CRC is away from its time-varying mean, the scored CRC (Z_{CRC}), is calculated by subtracting a time-varying mean and then dividing it by a time-varying standard deviation. As Chau and Deesomsak (2014) do, we calculate the time-varying mean by using the moving average of 50 days' values of the total credit risk connectedness and compute the time-varying standard deviation by taking the square root of a 50-day moving average of the squared deviations from the time-varying mean.[25] The second step is to classify the severity of CRC based on the values of Z_{CRC}. Specifically, we assign Z_{CRC} larger than 2 standard deviations (SD) above the mean to the 'severe CRC' category (regime A), Z_{CRC} falling between 0.75 and 2 SD to the 'moderate CRC' category (regime B), Z_{CRC} falling within +/-0.75 SD of the mean to the 'normal CRC' category (regime C), and Z_{CRC} below -0.75 SD of the mean to the 'below-normal CRC' category (regime D). Such a rating system is important as it could provide policymakers with a useful tool to monitor the

[24] Rochet and Tirole (1996) suggest that the existence of interbank exposures can encourage banks to monitor each other, which benefits the banking industry.
[25] We also use 60 and 100 days' values of the total credit risk connectedness to calculate the time-varying mean. The results related to Z_{CRC} remain qualitatively the same.

emerging vulnerabilities that caused by abnormal rises in credit risk spillovers across G-SIFIs, so that they can take timely actions to stabilise the global financial system.[26]

Figure 3.2 presents the movements of Z_{CRC} and the corresponding four regimes. As indicated in the figure, the majority of Z_{CRC} locate in regime C and regime D, with a few exceptions in regime B or even regime A. To investigate whether the peaks of Z_{CRC} (larger than 2) can provide an 'early warning' indicator for emerging financial crises, a chronology of severe financial events is constructed in Figure 3.3 and these catastrophes are marked with shaded areas. The chronology of critical financial events is constructed by referencing the 'Full Timeline' of the Federal Reserve Bank of St. Louis, Louzis and Vouldis (2013), as well as the relevant financial news. The figure indicates that Z_{CRC} has a high correlation to the occurrence of major financial episodes and many well-known financial crises occurred approximately at the peaks of Z_{CRC}. For instance, the peaks of Z_{CRC} are coincide with the liquidity stress and bank-run of Northern Rock (08/2007–09/2007), the collapse of Lehman Brothers (09/2008–10/2008), and the onset of the European sovereign debt crisis in the early 2010.

3.5.2.2 Total Directional Credit Risk Connectedness of G-SIFIs

As suggested by Alter and Beyer (2014) and Diebold and Yilmaz (2015b), the total credit risk connectedness of G-SIFIs can be divided into various components based on regions or institutional characteristics. Total connectedness of N firms is not a simple sum of all its components, but it is a weighted average of all the components. The

[26] It is noted that this classification approach is not without its shortcomings. For instance, there is no consensus on how many standard deviations the index has to exceed its mean in order to be classified as 'severe'. Nonetheless, the choices of thresholds are comparable to those commonly used in the literature (see, e.g., Chau and Deesomsak, 2014).

calculation approach of cross-region/group and within-region/group connectedness is described in Appendix 3A.

3.5.2.2.1 Cross-Region and Within-Region Connectedness

The sample firms are from three main regions: the EU (20 firms), the United States (9 firms) and Asia (3 firms). In Figure 3.4, Panel A presents credit risk connectedness originating from each region and Panel B demonstrates credit risk connectedness across any two regions. As indicated in Panel A, credit risk connectedness of the U.S. G-SIFIs fluctuates around 40% and reaches its peaks during three occasions. The first peak coincides the 2007–2008 global financial crisis period. The second spike occurs in mid-2011 when the U.S. federal government credit rating was downgraded from AAA to AA+. The final peak occurs in the second half 2014 when the 3rd quantitative easing was terminated and when six major banks (including HSBC, RBS, UBS, JP Morgan, Citi, and Bank of America) were heavily penalised by the U.K. and the U.S. regulators over attempted manipulation of foreign exchange rates.

Credit risk connectedness of the G-SIFIs in the EU fluctuates around 65%. Compared with those in the U.S., the EU G-SIFIs have a higher level of within-region linkages because there are more European banks on the list of G-SIFIs. Likewise, the within-region connectedness in the EU experienced several peaks in the 2007–2008 financial crisis. Moreover, in October 2010, the EU credit risk transmission reached to its highest level (88%). After that, accompanied by a series of rescue policies implemented by the European Central Bank (ECB) to curb the European sovereign debt crisis, the credit risk connectedness gradually declined to 47% in July 2012. However, the credit risk connectedness increased back to nearly 80% in 2013 and again in 2014.

With regards to the G-SIFIs in Asia, within-region credit risk connectedness of G-SIFIs is only 5% on average. One reason is that although there are around eight G-SIFIs from the Asia region on the FSB's official lists, only three of them can meet our data selection requirements. Another possible interpretation is that because of heavy regulation and government control, China's current economy may not be fully exposed to the risks posed by the global systemically important financial institutions. Therefore, the default probability of Bank of China may not be closely linked with that of the two Japanese G-SIBs. In addition, the credit risk connectedness of the Asian G-SIBs substantially increased when there was an earthquake in Japan in March 2011.

Regarding the cross-region transmission between the U.S. G-SIFIs and the EU G-SIFIs, on average, credit risk connectedness from the EU to the U.S. is around 13% and that from the U.S. to the EU is about 16% (Figure 3.4, Panel B). In general, the U.S. G-SIFIs are net credit risk senders. However, from late 2009 to mid-2011, credit risk spillovers from the EU to the U.S. was equal to or even higher than that from the U.S. to the EU. This seems to suggest that, during the European sovereign debt crisis, the EU G-SIFIs became net credit risk transmitters to the U.S. G-SIFIs. After that, the U.S. G-SIFIs played a key role in the global credit risk transmission once again. Our findings are slightly different from those of Diebold and Yilmaz (2015b), who study the cross-region stock volatility spillovers between the U.S. and the EU financial firms. They find that although the U.S. financial institutions played more important roles in transmitting stock volatility during the subprime crisis, the EU financial institutions continued to be the major risk providers from 2010 to 2014. Between the U.S. and Asia, while there are several unexpected outliers in the 'from' and 'to' directional connectedness series, the averages of the two series are less than 20%. As expected, the G-SIFIs in Asia are net credit risk receivers. Similar patterns can be seen from the cross-region connectedness between the EU G-SIFIs and the Asian G-SIFIs.

3.5.2.2.2 Cross-Group and Within-Group Connectedness

Figure 3.5 plots directional credit risk connectedness of G-SIFIs within and across two groups of global systemically important financial institutions, that is, G-SIBs (23 firms) and G-SIIs (9 firms). Panel A presents credit risk connectedness originating from each group and Panel B demonstrates credit risk connectedness between two groups. As shown in Panel A, credit risk connectedness within G-SIIs fluctuates around 26%, while that within G-SIBs moves around 66%. G-SIBs have a relatively higher within-group connectedness because they are closely linked by common credit exposure, interbank lending, and derivatives trading, while G-SIIs tend to operate more independently. The figure in Panel B indicates that credit risk transmission from G-SIBs to G-SIIs and that from G-SIIs to G-SIBs fluctuate around 18% and 16%, respectively. Although there is bilateral credit risk transmission between two groups, G-SIBs are generally net credit risk providers in the whole sample period, with an exception of only a few sub-intervals, such as the AIG bailout period in 2008. These results are generally consistent with those of Billio et al. (2013) and Chen et al. (2014).

3.5.3 Ranking of 'Too-Interconnected-To-Fail' G-SIFIs

Employing the dynamic net directional credit risk spillovers of individual G-SIFIs, this chapter derives a yearly ranking of 'too-interconnected-to-fail' G-SIFIs. It is important to provide this ranking because Chan-Lau (2010) suggests that regulators can penalise the G-SIFIs based on their degree of interconnectedness rather than their risk-weighted assets. Chan-Lau (2010) argues that such capital charges may effectively internalise the negative externalities related to highly interconnected institutions and encourage them to strengthen solvency and diversify counterparties in financial activities.

Table 3.11 provides a comparison of our ranking with the official list issued by the FSB in 2013 and in 2014.[27] The table shows that our G-SIBs' rankings are dissimilar to their official rankings. There are several differences between the 'too-interconnected-to-fail' ranking and the official list. First, the FSB's list contains only G-SIBs but our ranking includes both G-SIBs and G-SIIs. Hence, it may not be feasible to use the FSB list to empirically examine the interactions between G-SIBs and G-SIIs. Second, the newly proposed 'too-interconnected-to-fail' ranking is derived directly from CDS market data, while the official list is based on accounting data submitted by banks. Thus, our ranking is considered to be better reflecting market expectation of credit risk transmission across the G-SIFIs.[28] Moreover, by identifying the key players in the global default risk transmission, the 'too-interconnected-to-fail' ranking complements the FSB list which focuses largely on G-SIBs' general business risk, as measured by size, substitutability, complexity, interconnectedness, and cross-jurisdictional activity.

While the 'too-interconnected-to-fail' ranking is not designed to replace the FSB list, regulators can combine it with the official list to construct a 'composite' ranking that considers various sources of information about G-SIBs (including both balance-sheet information and market data) in order to capture the multiple facets of systemic risk. To achieve this, this chapter suggests the following three steps. First, for each G-SIB,

[27] To make the comparison, the G-SIIs on our 'too-interconnected-to-fail' ranking are excluded. The purpose of making this comparison is to complement the current understanding of systemic importance of individual G-SIBs from the perspective of their roles in default risk transmission rather than to prove that our ranking can substitute the official list. However, it would be interesting to complete the empirical analysis by examining the determinants of the ranking suggested by the official list in our future research.
[28] Although the V-Lab of the New York University also provides a ranking of global large financial institutions based on SRISK, the calculation of SRISK relies on both balance-sheet data and a long-run marginal expected shortfall (LRMES) estimator. Thus, similar to the FSB's list, the ranking of V-Lab is not entirely based on market data.

we add the yearly average net directional credit risk connectedness values to the yearly interconnectedness scores. Then, we use the new scores of interconnectedness and the scores of size, substitutability/financial institution infrastructure, cross-jurisdictional activity, and complexity to calculate an equally weighted average scores of individual G-SIBs. Finally, based on the equally weighted average scores, a yearly 'composite' ranking of G-SIBs can be obtained. The 'composite' ranking of G-SIBs in 2013 and 2014 are presented in Table 3.11.[29] Although the G-SIB rankings on the 'composite' ranking are still rather distinct from that on the official list, the extra loss absorbency bucket allocation of each G-SIB remains largely unchanged. The major advantage of this 'composite' ranking is that it considers not only market participants' judgement associated with systemic credit risk importance of G-SIBs, but also the business activity interconnections among those large banks.

3.5.4 Determinants of the 'Too-Interconnected-To-Fail' Ranking

As suggested by the unreported results of preliminary F-test, Breusch-Pagan Lagrange multiplier (LM) test, and Hausman test, the regressions for G-SIBs are estimated by using the random-effects GLS method.[30] To adjust for heteroskedasticity, we employ robust standard errors. Estimation results are reported in Table 3.12. As indicated in this table, banks with a higher level of interbank loans tend to play more important roles in the global credit risk spillovers. This finding is consistent with Hypothesis 1(a) and Chan-Lau's (2010) argument that the interconnectivity across financial institutions can be largely attributable to their extensive interbank business. Financial distress of one financial firm which has more interbank exposure can materially increase the likelihood

[29] The scores of G-SIBs in 2013 and 2014 are available at the website of the Office of Financial Research (financialresearch.gov/gsib-scores-chart/files/OFRbr-2016-04-13-gsib-data.xlsx).
[30] According to Park (2011), F-test is used to choose between pooled OLS model and fixed-effects model, Breusch-Pagan Lagrange multiplier (LM) test is used to choose between pooled OLS model and random-effects model, and Hausman test is employed to choose between fixed and random effects models.

of distress of other financial institutions via the interbank lending network. Also, banks with more non-interest income are associated with higher systemic credit risk and are more likely to transmit credit risk shocks to their peers, which supports Hypothesis 1(b). Similar findings are also documented by Brunnermeier et al. (2012), who suggest that banks' non-interest income can significantly and positively affect their systemic risk measured by MES and ΔCoVaR.

Moreover, Hypothesis 1(c) is not fully supported by the results of the impact of capital adequacy. Tier 1 leverage ratio and leverage ratio are negatively related to G-SIB's systemic credit risk importance, while Tier 1 capital ratio and capital adequacy ratio are insignificant and positive with regard to G-SIB's credit risk connectedness. The only difference between Tier 1 leverage ratio (leverage ratio) and Tier 1 capital ratio (capital adequacy ratio) is the denominator in their calculations. Leverage ratios are based on gross assets, while capital ratios are based on risk-weighted assets. The effectiveness of the risk-weighted scheme has been widely questioned by researchers. For example, Demirgüç-Kunt et al. (2013) argue that the Basel II relies heavily on external credit rating agencies, whose objectivity is criticised, to determine risk weights and approves large banks to use their own capital calculation models, which are not transparent and inconsistent across banks. Also, as pointed out by the BCBS (2009), the risk adjustment under the Basel rules is subject to manipulation and some large banks can show strong capitalisation but actually possess insufficient tangible common equity which is the core component of regulatory capital absorbing unexpected losses. To complement the current capital requirements, the Basel III proposes a Tier 1 leverage ratio requirement. As discussed by Fender and Lewrick (2015), the leverage ratio shows greater robustness against risks and uncertainties than the risk-adjusted framework and its calculation is simple. The findings of this chapter provide support to the effectiveness of leverage ratios, especially Tier 1 leverage ratio, and suggest that they may effectively curb G-SIBs to transmit credit risk shocks to their peers.

Additionally, in line with Hypothesis 1(d), the positive coefficients of additional loss absorbency bucket suggest that a higher extra loss absorbency bucket allocated to a G-SIB is more likely to be perceived as bad news by investors and is accompanied by an increase in the 'too-interconnected-to-fail' ranking of the G-SIB. This result signals the suspicion about whether the stricter capital regulation initiative can effectively motivate banks to reduce excessive risk-taking and eliminate public expectations of bank bailouts. The similar doubt is raised by Bongini et al. (2017), who use an event study to test stock price reactions and default risk evolutions of large insurers to the release of information regarding G-SIIs. Bańbuła and Iwanicz-Drozdowska (2016) show that the releases of the lists of G-SIBs substantially and significantly reduce the systemic importance of G-SIBs. However, unlike this chapter, they use stock data and systemic importance index obtained from multivariate extreme value theory. Also, they do not consider the effect of extra loss absorbency bucket allocations on G-SIBs' systemic relevance.

Again, as informed by the unreported results of preliminary F-test and Breusch-Pagan Lagrange multiplier (LM) test, the regressions for G-SIIs are estimated by using pooled OLS method and heteroskedasticity is controlled for. The estimation results shown in Table 3.13 support Hypothesis 2(a) and 2(b). Specifically, the G-SII having more other income has a higher 'too-interconnected-to-fail' ranking. The larger G-SIIs, measured by total assets, tend to be more systemic important, supporting the argument of Acharya et al. (2009). These results are in line with those of Weiß and Mühlnickel (2014), Bierth et al. (2015), and Irresberger et al. (2016). Another finding is that G-SIIs relying heavily on international sales are more important in credit risk transmission. However, Weiß and Mühlnickel (2014) and Bierth et al. (2015) do not find significant impact of global activities on insurers' systemic risk. One possible reason is that they use the systemic risk measures which focus on either exposure or contribution to systemic risk, while we use the measures which concentrate on linkages among financial institutions.

3.5.5 Additional Analysis and Robustness Test

In this section, some additional analyses are conducted and the robustness of the results are examined by implementing different econometric specifications, estimation method, rolling window, and forecasting horizon. First, this study follows Brunnermeier et al. (2012) to divide non-interest income into trading account income and other non-interest income, e.g., investment banking/venture capital income. The results reported in Table 3.14 and 3.15 suggest that trading income is positively related to G-SIB's systemic risk importance, while the effect of other non-interest income is largely insignificant. Such findings are fairly in line with the results of Brunnermeier et al. (2012), who find that compared with investment banking/venture income, trading income contributes slightly more to banks' systemic risk. Then, to check the robustness of rolling window size and prediction horizon, a 150-day rolling window and 10-day forecast horizon are used, respectively. The main empirical findings on dynamics and determinants of credit risk connectedness of G-SIFIs remain qualitatively unchanged.

We use GMM method to re-estimate main regressions to mitigate possible endogeneity concern. The results in Table 3.16 confirm that the general conclusions remain valid. Finally, it is noted that the dependent variable of our main regressions is the ranking of each G-SIFI that is discrete and ordinal in nature. Hence, we use random-effects ordinal logit and probit models to alleviate the concern that the non-continuous and ordinal nature of the dependent variable may cause significant bias in the regression results.[31] However, as reported by Table 3.17, the sign and statistical significance of the ordinal logit and probit coefficients generally agree with the results of linear panel regressions reported in Section 3.5.4.

3.6 Conclusions

This chapter investigates credit risk transmission across the G-SIFIs from 2006 to 2014. Diebold and Yilmaz's (2015a) VECM-based connectedness measures are used to allow for the existence of long-run equilibrium relations shared by credit risk of G-SIFIs. We put forward a new yearly ranking of 'too-interconnected-to-fail' G-SIFIs to identify the credit risk transmitters and the credit shock receivers in the global financial system. Finally, the factors affecting G-SIFI's systemic credit risk importance are examined.

This study finds that the empirical results generated by using VECM and VAR models are not dissimilar to each other. The total credit risk connectedness (CRC) among G-SIFIs increases considerably during the 2007–2008 financial crisis and then continues to fluctuate around 90% until 2014. To assess the extent to which the intensified credit risk transmission of G-SIFIs would threaten the global financial stability, a scored CRC (Z_{CRC}) is computed to monitor how many standard deviations the current CRC is away from its time-varying mean. The peaks of Z_{CRC} allow one to derive a timely indicator for financial crises and reliably locate and date significant financial episodes that are of serious concerns to market regulators and financial experts. Moreover, as shown in the cross-region/group and within-region/group analysis, the G-SIFIs from the U.S. are the major global credit risk transmitters to their peers in the EU and Asia. Although there

[31] According to Torres-Reyna (2012), although ordinal logit and ordinal probit regressions share the same model specifications, they use different functions to define the predictors of dependent variables. Logit models use the cumulative distribution function of the logistic distribution, while probit models use the cumulative distribution function of the standard normal distribution. Thus, we use both models.

is bilateral credit risk transmission between G-SIBs and G-SIIs, the G-SIBs are the net credit risk senders (except for the AIG distress period).

Central bankers and regulators can combine the proposed ‘too-interconnected-to-fail’ ranking with the official list published by the FSB to construct a ‘composite’ ranking which considers both the accounting information and the CDS market data. Interbank lending, non-conventional banking activity (especially trading business), and extra loss absorbency requirement bucket are all found to be positively associated with G-SIB’s credit risk transmission. Unlike Tier 1 capital ratio and capital adequacy ratio, Tier 1 leverage ratio and leverage ratio are negatively related to G-SIB’s credit risk spillovers, lending support to the recently proposed Basel III Tier 1 leverage ratio requirement. The G-SII with more non-traditional non-insurance business, larger size, and more global sales tends to play a more significant role in sending credit risk shocks.

Table 3.1: Summary of Market-Based Systemic Risk Measures

Measures	Studies	Descriptions	Advantages	Disadvantages
Contribution to the variance of the systemic Expected shortfall (EXSHORT)	Lehar (2005)	EXSHORT defines one firm's systemic risk as its share of the total volatility of the expected shortfall for the system which equals the total present value of the amount of debt that cannot be covered by the assets of the distressed firms under a hypothetical regulator's supervision.	It uses public information of financial markets, e.g., stock price and balance-sheet information. When define the likelihood of systemic crisis, it considers the size of the distressed firm and the number of banks which default simultaneously.	It may not consider off-balance sheet information which is important for financial institutions; it may not account for one firm's failure in the circumstance that the system is already in distress (Brownlees and Engle, 2017).
Marginal Expected Shortfall (MES)	Acharya, Pedersen, Philippon, and Richardson (2017)	MES tracks the sensitivity of a firm's return to a market-wide extreme event and measures a firm's systemic risk exposure by conditioning firm's distress on market's distress.	It is a simple market-based measure of a firm's fragility and uses only stock prices. Also, it is a weighted and directional measure (Diebold and Yilmaz, 2014).	MES cannot assess the likelihood of firm distress which is determined by not only MES but also the amount of the capital held by firms to buffer the loss caused by adverse market movements (Diebold and Yilmaz, 2014). It does not consider firm-specific attributes, e.g., size and leverage (Banulescu and Dumitrescu, 2015).
SRISK	Acharya, Engle, and Richardson (2012); Brownlees and Engle (2017)	SRISK is defined as the expected capital shortfall of a financial firm conditional on the distress of market.	It considers dependence among firms, size, and leverage (Acharya et al., 2017). It uses public information of financial markets, e.g., stock price and balance-sheet information.	Its calculations rely on the variables sampled at different frequencies (Banulescu and Dumitrescu, 2015). Also, it may not consider off-balance sheet information which is important for financial institutions (Brownlees and Engle, 2017).
Component Expected Shortfall (CES)	Banulescu and Dumitrescu (2015)	CES is the product of MES and the relative market capitalisation of a financial institution. It measures the absolute sensitivity of a firm to systemic risk.	It accounts for the size of a firm; it uses only daily financial market data; unlike MES, the ES of the financial system at time t equals the sum of CES for all the firms in the system (Banulescu and Dumitrescu, 2015).	Its calculations may be affected by the choice of weighting scheme. Also, like MES, it cannot assess the likelihood of firm distress which is determined by not only MES but also the amount of the capital held by firms to absorb the loss caused by market downturns.

Table 3.1: Summary of Market-Based Systemic Risk Measures (Continued)

Measures	Studies	Descriptions	Advantages	Disadvantages
Conditional Value-at-Risk (CoVaR) and ΔCoVaR	Adrian and Brunnermeier (2016)	CoVaR measures the value-at-risk of the financial system conditional on the distress of a financial firm. $\Delta CoVaR^{j\|i}$ measures the difference between firm-j VaR when firm-i is 'heavily' stressed and firm-j VaR when firm-i is in "normal" times. ΔCoVaR indicates a firm's contribution to systemic risk.	CoVaR and its variations are useful measures of tail-event linkages between financial institutions (Adrian and Brunnermeier, 2011). Also, ΔCoVaR is weighted and directional systemic risk measures (Diebold and Yilmaz, 2014).	They do not consider firm-specific attributes, e.g., size and leverage (Acharya et al., 2017).
Distressed insurance premium (DIP)	Huang, Zhou, and Zhu (2009, 2012); Black, Correa, Huang, and Zhou (2016)	DIP is the hypothetical insurance premium required to cover distressed losses in the financial system and is a function of probability of default (PoD) of individual firm and asset correlations among firms. The systemic importance of each firm is its marginal contribution to the DIP.	It is applicable to any firms with publicly tradable equity and CDS contracts; the probability of default is risk-neutral and forward looking; it does not depend on any accounting information (Huang et al., 2009).	CDS data may not be available for a long time period and a large sample of firms (Zhang et al., 2015).
CATFIN	Allen, Bali, and Tang (2012b)	It is a measure of aggregate systemic risk. It is calculated as the average of three VaR measures at the 99% confidence level. The three VaR measures are estimated by Generalised Pareto distribution, Skewed Generalised Error distribution, and a nonparametric method.	It can forecast macroeconomic downturns six months into the future; it can be combined with VaR and ES methods (Allen et al., 2012b).	The predictive advantage of this measure only exists within banking sectors, but not within nonfinancial firms or simulated "fake banks" (Allen et al., 2012b).
Shapley values	Drehmann and Tarashev (2011)	Two Top-down measures are designed based on Shapley values: Participation approach (PA) and Contribution approach (CA). One Bottom-up measure: Bottom-up approach (BA).	Shapley values consider both the firm systemic risk contribution and firm systemic risk exposure.	Due to high dimensionality issue, the applications of Shapley values are limited to small samples of firms (Zhang et al., 2015).

Table 3.1: Summary of Market-Based Systemic Risk Measures (Continued)

Measures	Studies	Descriptions	Advantages	Disadvantages
Conditional Co-Risk	Chan-Lau, Espinosa, Giesecke, and Solé (2009)	It measures the proportional rise in a firm's credit risk induced, directly and indirectly, by its links to another firm in the system.	It examines the direct and indirect credit risk co-dependence across firms for different quantiles; it is more informative than unconditional risk measures; the quantile regression considers nonlinearity in co-movements of firms (Chan-Lau et al., 2009).	Its usefulness depends on whether market is efficient (Chan-Lau et al., 2009).
Realized systemic risk beta	Hautsch, Schaumburg, and Schienle (2014)	It is defined as the total time-varying marginal effect of a firm's VaR on the system's VaR.	It considers network spillover effects across firms' tail risk exposures; it depends on only public accessible data (Hautsch et al., 2014).	Since it is essentially a VaR-type measure, it suffers from the same critiques as VaR does, e.g., it is not a coherent risk measure since it violates the sub-additivity property.
Connectedness Measures	Billio, Getmansky, Lo, and Pelizzon (2012)	PCA is used to estimate the number and importance of common factors driving asset returns of financial institutions. Pairwise Granger-causality is used to identify network of statistically significant Granger-causal relations.	These measures rely on fewer assumptions than variance-decomposition and impulse response analyses; they are directional (Diebold and Yilmaz, 2014). They provide direct estimates of the statistical connectivity of a network of financial firms' returns by linear Granger causality and volatility by nonlinear Granger causality (Billio et al., 2012).	They are exclusively pairwise and unweighted, testing zero vs. nonzero coefficients, with arbitrary significance levels, and without tracking the magnitude of non-zero coefficients (Diebold and Yilmaz, 2014). Also, it may be difficult to clearly interpret Granger causality test results unless all the shocks are simultaneously considered (Acharya et al., 2017).
Network-based Connectedness Measures	Diebold and Yilmaz (2014)	Forecast error variance decompositions are used to define different levels of connectedness, from pairwise to system-wide.	They are weighted directed measures; they are more general than correlation-based measures which are only pairwise (Diebold and Yilmaz, 2014). They only depend on the information of asset prices or volatility.	These measures cannot identify risk exchange centres as Yang and Zhou (2013) do. Also, to identify uncorrelated structural shocks from correlated reduced-form shocks, assumptions must be made before conducting variance decomposition and impulse response analysis (Diebold and Yilmaz, 2014).

Notes: This table summarises the major market-based systemic risk measures. Each measure may have several extensions, but they are not included in this table.

Table 3.2: Summary of Empirical Evidence of Connectedness of Financial Firms

Studies	Markets	Methodologies	Major Findings
Billio, Getmansky, Lo, and Pelizzon (2012)	Monthly Stock Data; 25 hedge funds, banks, broker/dealers, and insurance companies around the world	Connectedness measures developed based on PCA, linear Granger causality and Nonlinear Granger causality.	Since all four sectors have become highly interrelated through a complex and time-varying network over the recent decade, the level of systemic risk in the finance and insurance industries is increased. Their connectedness measures can date and quantify financial crisis times, and can be considered as predictors of financial market conditions. Also, compared with other financial firms, banks are primary senders of shocks via lending and trading activities.
Yang and Zhou (2013)	Daily CDS Data; 43 largest financial institutions across the world	Cluster analysis, principal component analysis (PCA), the direct acyclic graph (DAG) and structural VAR analysis	Financial institutions are classified into three groups, credit risk senders, credit risk exchange centres and credit risk receivers. The former two groups of financial institutions can be considered as G-SIFIs, while the last group cannot be G-SIFIs. Short-term debt ratios are significant determinants of different roles of financial firms in credit risk transfer. However, corporate governance indexes, size, liquidity, and write-downs cannot explain the different risk transfer roles played by these financial institutions.
Drehmann and Tarashev (2013)	Balance-sheet Data; One banking system with nine hypothetical banks and another with 20 real-world banks	Shapley values: Participation approach (PA) and generalised contribution approach (GCA).	They find that interconnectedness is a key driver of systemic risk. However, since PA and GCA reflect the impact of interbank borrower and lender on system-wide risk differently, they can generate different results about which banks are systemically important.
Billio, Getmansky, Gray, Lo, Merton, and Pelizzon (2013)	Monthly CDS data; 17 Sovereigns, 63 banks, and 39 insurance companies around world	Connectedness measures developed based on PCA, linear Granger causality and Nonlinear Granger causality.	The system of banks, insurance companies, and sovereigns is highly connected. Sovereign risk seems to become relevant before the 2010-2012 European Sovereign crisis. Also, the proposed connectedness measures can be early warning signals and indicate the complexity of the financial system.
Chen, Cummins, Viswanathan, and Weiss (2014)	Daily CDS data and intraday stock data; 11 insurance firms and 22 banking firms around world	Huang, Zhou, and Zhu’s (2009, 2012) DIP and Linear and non-linear Granger-causality tests.	Bidirectional Granger causality are found between banks and insurers. However, after controlling for conditional heteroskedasticity, banks exert stronger and longer duration impact on insurers than vice versa.

Table 3.2: Summary of Empirical Evidence of Connectedness of Financial Firms (Continued)

Studies	Markets	Methodologies	Major Findings
Diebold and Yilmaz (2014)	Intraday Stock Data; 13 US financial institutions	Diebold and Yilmaz's (2014) network-based connectedness measures.	Financial institutions' To-degree connectedness and From-degree connectedness can track their systemic importance during different time periods. Total-degree connectedness shows two big cycles which indicate dot-com bubble and 2007-2008 financial crises. Also, the total-degree measure can reflect the effects of critical events on the U.S. financial system, such as the Lehman Bankruptcy.
Hautsch, Schaumburg, and Schienle (2014)	Daily Stock Data; Publicly traded US depositories (21), broker dealers (7), insurers (20), and other firms (11)	Hautsch et al.'s (2014) realized systemic risk beta	A high degree of tail risk interconnectedness of the U.S. financial system is found. Direct credit and liquidity exposure are potential channels of risk spillovers. Firms can be classified into major risk producers, transmitters, or recipients within the system. Large depositories are the most systemically important.
Bierth, Irresberger, and Weiß (2015)	Daily Stock Data; 253 insurers in the world, including 112 life insurers and 141 non-life insurers	Billio et al.'s (2012) connectedness measures	Systemic risk in the global insurance sector is smaller than that in the global banking sector. However, both the exposure and contribution of insurers to the fragility of the whole financial system have raised since the recent financial crisis. Compared with other insurers, the nine G-SIIs have significantly larger size and are more interconnected. Also, interconnectedness, size, loss rations, funding fragility, and leverage can determine an insurer's systemic risk.
Diebold and Yilmaz (2015b)	Daily Stock Data; 28 financial institutions in the US and the EU	Diebold and Yilmaz's (2014) network-based connectedness measures	During the 2007-2008 financial crisis, stock volatility spillovers from the U.S. to the EU. After that, bidirectional spillovers are documented in late 2008. After June 2011, the EU financial institutions become the net risk transmitters because of the European sovereign debt crisis.
Elyasiani, Kalotychou, Staikouras, and Zhao (2015)	Daily Stock Data; Banks and insurers (life and non-life) from the US, the EU and Japan	VAR-BEKK model which can detect return and volatility transmission simultaneously	From 2003 to 2009, they document substantial return and volatility transmissions within and across banking and insurance industries. The U.S. financial firms play important roles in spreading risk to their peers in other countries. Size and leverage are major factors to determine return contagion among the major banking firms.

Notes: This table summarises the previous empirical evidence of connectedness of financial firms.

Table 3.3: Determinants of the 'Too-Interconnected-To-Fail' Ranking (G-SIBs)

Variables	Proxies	Data Source
Interbank activity	Log of inter-bank loans (US$)	DataStream
No-deposit business	Ratio of non-interest income to total interest income; ratio of trading income to total interest income; ratio of other non-interest income to total interest income	DataStream
Capital adequacy	Tier 1 leverage ratio (ratio of Tier 1 capital to total assets) (%); Tier 1 capital ratio (ratio of Tier 1 capital to total risk-weighted assets) (%); leverage ratio (ratio of the sum of Tier 1 and Tier 2 capital to total assets) (%); capital adequacy ratio (ratio of the sum of Tier 1 and Tier 2 capital to total risk-weighted assets) (%)	DataStream
Extra loss absorbency requirement bucket	It is a variable ranging from 0 to 5. The higher value means the higher extra loss absorbency requirement bucket	Official lists published by the FSB
Global activity	Ratio of foreign sales to total sales (%)	DataStream
Corporate Governance	Log of board size	DataStream
Leverage	Ratio of total debt to total asset (%)	DataStream
Size	Log of total assets (US$)	DataStream
Credit risk	Ratio of non-performing loans to total loans (%)	DataStream
Management effectiveness	Return on Equity (%)	DataStream
Deposit Insurance Policy	Coverage limit GDP per capita (%)	Demirgüç-Kunt et al. (2014)
Country characteristic	GDP growth rate (%)	The World Bank Database
Financial condition in one region	Bloomberg Financial Condition Index	Bloomberg

Notes: This table reports the drivers, their proxies, and data sources of the 'too-interconnected-to-fail' rankings of G-SIFIs (G-SIBs).

Table 3.4: Determinants of the 'Too-Interconnected-To-Fail' Ranking (G-SIIs)

Variables	Proxies	Data Source
Global activity	Ratio of foreign sales to total sales (%)	DataStream
Non-policyholder liabilities	Ratio of total liability to total insurance reserves	DataStream
Size	Log of total assets (US$); log of market capitalisation (US$)	DataStream
Other income	Other pre-tax income and expenses besides operating income, non-operating interest income, interest expense on debt, interest capitalized, pre-tax extraordinary charge, pre-tax extraordinary credit and increase/decrease in reserves (US$)	DataStream
G-SII Designation	It is a dummy variable which equals 1 after one insurer identified as a G-SII and 0 otherwise.	Official lists published by the FSB
Corporate Governance	Log of board size	DataStream
Quality of insurance portfolio	Loss ratio (claim and loss expense plus long term insurance reserves divided by premiums earned) (%)	DataStream
Leverage	Ratio of total debt to total asset (%)	DataStream
Investment success	Ratio of investment income to net revenue (%)	DataStream
Operating efficiency	Ratio of operating expenses to total assets	DataStream
Management effectiveness	Return on Equity (%)	DataStream
Financial condition in one region	Bloomberg Financial Condition Index	Bloomberg
Country characteristic	GDP growth rate (%)	The World Bank Database

Notes: This table reports the drivers, their proxies, and data sources of the 'too-interconnected-to-fail' rankings of G-SIFIs (G-SIIs).

Table 3.5: Summary Statistics of CDS Spreads

	Mean	Std.	Min.	Max.
G-SIBs				
HSBC	70.343	41.048	4.950	181.895
Barclays	104.538	65.104	5.400	282.520
BNP Paribas	91.284	71.141	5.000	354.375
Deutsche Bank	90.632	52.053	8.850	299.725
Credit Suisse	86.827	50.849	9.400	259.250
Royal Bank of Scotland	137.864	93.967	3.500	396.935
Crédit Agricole	112.178	83.139	5.500	394.560
ING Bank	95.043	64.052	4.050	268.280
Santander	136.267	102.825	7.150	433.395
Société Générale	117.455	91.966	5.800	430.687
UBS	94.538	65.362	4.000	356.667
Commerzbank	110.561	76.095	7.450	350.975
Dexia	284.124	236.111	6.500	954.162
Lloyds Banking Group	123.851	92.752	3.750	381.575
JP Morgan Chase	78.373	40.621	11.000	227.280
Citigroup	140.578	111.055	6.900	645.000
Bank of America	125.443	93.629	7.900	480.710
Goldman Sachs	134.232	89.238	18.250	590.410
Morgan Stanley	171.297	137.741	17.250	1,197.010
Wells Fargo	76.882	48.644	6.000	297.750
Mitsubishi UFJ FG	51.384	35.382	7.800	204.230
Sumitomo Mitsui FG	64.603	42.551	5.450	200.905
Bank of China	128.163	81.861	14.350	450.000
G-SIIs				
Allianz	66.815	37.464	5.550	185.000
Assicurazioni Generali	129.983	106.163	5.500	438.045
Aviva	111.200	72.822	5.550	498.333
Axa	120.263	86.064	8.500	383.470
Prudential	121.233	123.261	7.250	922.500
MetLife	175.022	164.734	10.200	940.582
Prudential Financial	178.330	196.188	10.200	1,314.100
AIG	307.357	474.851	8.000	4,639.046
Aegon	148.961	101.466	8.350	557.500

Notes: This table presents the summary statistics of CDS Spreads in the sample. The sample period is from 02/01/2006 to 31/12/2014. The credit spreads are expressed in basis points.

Table 3.6: Augmented Dickey-Fuller (ADF) Unit-Root Test

Name of Firms	CDS spreads	CDS returns	Name of Firms	CDS spreads	CDS returns
Aegon	-1.785	-11.540***	Goldman Sachs	-2.162	-13.749***
AIG	-1.517	-13.036***	HSBC	-1.836	-12.870***
Allianz	-1.632	-14.298***	ING Bank	-1.856	-12.302***
Assicurazioni Generali	-1.553	-13.232***	JP Morgan Chase	-1.970	-14.065***
Aviva	-1.685	-12.643***	Lloyds Banking Group	-1.669	-13.148***
Axa	-1.658	-12.607***	MetLife	-1.548	-11.533***
Bank of America	-1.764	-13.523***	Mitsubishi UFJ	-2.484	-11.154***
Bank of China	-2.127	-12.126***	Morgan Stanley	-2.070	-13.153***
Barclays	-1.959	-13.521***	Prudential Financial	-1.570	-11.868***
BNP Paribas	-1.791	-13.945***	Prudential	-1.717	-10.779***
Citigroup	-1.799	-13.933***	Royal Bank of Scotland	-1.740	-13.643***
Commerzbank	-1.753	-13.586***	Santander	-1.966	-14.655***
Crédit Agricole	-1.831	-12.861***	Société Générale	-1.795	-13.020***
Credit Suisse	-1.936	-12.981***	Sumitomo Mitsui FG	-1.976	-14.857***
Deutsche Bank	-1.865	-14.507***	UBS	-1.844	-11.950***
Dexia	-1.951	-11.632***	Wells Fargo	-1.966	-13.417***

Notes: This table reports the t-statistics of Augmented Dickey-Fuller (ADF) unit-root test on CDS spreads and CDS returns. The critical values at significance level 1% (***), 5% (**), and 10% (*) are -3.436, -2.863, and -2.568, respectively.

Table 3.7: Johansen Cointegration Test

Rank	Eigenvalue	Log likelihood for rank	Trace test
0	-	194013.7	2839.94*** (0.000)
1	0.130	194177.3	2526.11*** (0.000)
2	0.118	194324.6	2243.67*** (0.000)
3	0.097	194444.6	2013.46*** (0.000)
4	0.089	194554	1803.6*** (0.000)
5	0.076	194646.9	1625.44** (0.010)
6	0.068	194729	1467.9 (0.085)
7	0.062	194803.7	1324.62 (0.289)

Notes: This table reports the test results of Johansen cointegration tests. Based on Schwarz Information criterion (SBC), the optimal lag is 3. Figures in the parentheses are the p-values. *** and ** denote statistically significant at 1% and 5%, respectively. The number of long-run cointegration relations is chosen based on significance level 5%.

Table 3.8: Summary Statistics of Determinants of the ‘Too-Interconnected-To-Fail’ Ranking

	N	Mean	Std.	Min.	Max.
Panel A: Summary Statistics of Drivers of ‘Too-Interconnected-To-Fail’ Ranking of G-SIBs					
Log of inter-bank loans	143	7.69	0.53	5.08	8.66
Non-interest income/total interest income	172	0.64	0.38	-0.16	2.61
Trading account income/total interest income	156	0.10	0.15	-0.49	0.78
Other non-interest income/total interest income	146	0.55	0.34	-0.19	2.48
Tier1 leverage ratio (%)	182	4.25	1.80	1.41	9.21
Tier1 capital ratio (%)	181	10.96	2.97	6.44	21.40
(Tier 1 + Tier 2)/total asset (%)	178	5.82	2.40	1.71	11.69
Capital adequacy ratio (%)	183	14.19	3.03	8.50	25.20
Buckets corresponding to the additional loss absorbency requirements	207	0.42	0.98	0.00	4.00
Foreign sales/total sales (%)	195	24.32	18.04	-19.64	82.92
Log of board size	203	2.54	0.51	0.90	3.26
Total debt/total asset (%)	207	27.57	13.56	4.53	61.16
Log of total asset	207	9.16	0.20	8.46	9.68
Non-performing loans/total loans (%)	160	3.31	9.44	0.16	119.52
Return on Equity (%)	206	2.95	55.39	-687.29	35.85
Coverage limit GDP per capita (%)	207	251.59	139.20	0.00	518.00
GDP growth rate (%)	207	1.62	2.83	-5.64	14.20
BFCI Index	207	-0.80	1.55	-4.13	1.27
Panel B: Summary Statistics of Drivers of ‘Too-Interconnected-To-Fail’ Ranking of G-SIIs					
Total liability/total insurance reserves	81	1.79	0.46	1.07	3.06
Other income/100,000	81	1.63	21.23	-25.27	179.45
Log of total asset	81	8.79	0.15	8.51	9.14
Log of market capitalisation	81	7.52	0.31	6.61	8.27
Foreign sales/total sales (%)	77	47.49	21.61	-21.78	90.99
G-SII dummy	81	0.10	0.30	0.00	1.00
Log of board size	81	1.13	0.09	0.90	1.38
Loss ratio (%)	81	115.38	40.54	-57.61	220.26
Total debt/total asset (%)	81	6.57	6.18	1.41	42.01
Investment income/net revenue (%)	81	0.29	0.31	0.03	2.92
Operating expenses/total assets	81	0.12	0.05	-0.04	0.22
Return on Equity (%)	79	5.18	34.04	-207.00	32.97
BFCI Index	81	-0.89	1.61	-4.13	1.11
GDP growth rate (%)	81	1.06	2.20	-5.62	4.08

Notes: This table presents the summary statistics of determinants of ‘too-interconnected-to-fail’ ranking of G-SIBs in Panel A and those of G-SIIs in Panel B.

Table 3.9: Pairwise Correlations of Determinants of the 'Too-Interconnected-To-Fail' Ranking

Panel A: Pairwise Correlations of Determinants of 'Too-Interconnected-To-Fail' Ranking of G-SIBs																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. IBL	1.00																	
2. NII	-0.13	1.00																
3. TAI	-0.07	0.53	1.00															
4. ONII	0.06	0.60	0.15	1.00														
5. T1LR	-0.17	0.00	-0.08	0.04	1.00													
6. T1CR	-0.18	0.05	0.23	0.01	0.14	1.00												
7. LR	-0.17	0.07	-0.06	0.01	0.95	-0.06	1.00											
8. CR	-0.29	0.08	0.29	-0.08	0.19	0.92	0.05	1.00										
9. ALA	0.07	0.17	0.09	0.18	0.23	0.43	0.11	0.36	1.00									
10. FS	-0.06	-0.01	0.29	0.03	-0.10	0.24	-0.17	0.27	0.12	1.00								
11. BS	0.21	-0.23	-0.15	-0.08	0.01	0.12	-0.06	0.11	0.09	-0.04	1.00							
12. L	-0.03	-0.47	-0.14	-0.36	-0.18	0.06	-0.19	0.05	-0.16	-0.23	-0.01	1.00						
13. A	0.33	0.22	0.04	0.18	-0.04	-0.01	-0.06	0.00	0.22	0.27	0.26	-0.47	1.00					
14. NP	0.02	0.03	-0.05	0.01	0.16	0.23	0.06	0.17	0.09	0.05	0.01	-0.12	0.05	1.00				
15. ROE	-0.02	0.23	0.13	-0.02	0.10	-0.23	0.15	-0.16	0.01	0.22	-0.09	-0.13	0.18	0.02	1.00			
16. DI	0.03	0.31	0.15	0.24	0.43	0.22	0.40	0.19	0.34	-0.09	0.10	-0.03	0.16	0.11	-0.07	1.00		
17. GDP	0.08	-0.19	-0.12	-0.02	0.16	-0.12	0.12	-0.13	-0.02	-0.03	-0.10	-0.06	-0.18	-0.12	0.10	-0.22	1.00	
18. BFCI	-0.19	0.18	0.20	0.15	0.11	-0.12	0.14	-0.11	0.14	0.03	-0.36	-0.03	-0.24	-0.05	0.17	0.05	0.48	1

Table 3.9: Pairwise Correlations of Determinants of the 'Too-Interconnected-To-Fail' Ranking (Continued)

Panel B: Pairwise Correlations of Determinants of 'Too-Interconnected-To-Fail' Ranking of G-SIIs														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Foreign sales/total sales	1.00													
2. Total liability/total insurance reserves	0.10	1.00												
3. Log of total asset	-0.02	0.10	1.00											
4. Log of market capitalisation	-0.10	0.09	0.04	1.00										
5. G-SII dummy	-0.27	-0.15	-0.20	0.46	1.00									
6. Other income	-0.03	-0.10	-0.04	0.08	0.19	1.00								
7. Log of board size	-0.12	-0.47	-0.03	0.09	0.37	-0.05	1.00							
8. Loss ratio	0.21	0.19	-0.03	-0.42	-0.15	-0.05	-0.28	1.00						
9. Total debt/total asset	-0.15	0.30	0.21	0.37	0.10	-0.08	-0.09	-0.19	1.00					
10. Investment income/net revenue	-0.44	-0.13	-0.01	-0.26	-0.11	0.00	0.00	-0.31	-0.03	1.00				
11. Operating expenses/total assets	0.46	-0.52	-0.05	-0.09	0.07	0.03	0.37	0.14	-0.23	-0.42	1.00			
12. Return on Equity	-0.09	0.04	-0.01	-0.16	0.57	0.05	0.26	0.18	-0.27	0.01	0.04	1.00		
13. BFCI Index	-0.09	0.16	0.04	-0.01	0.47	0.28	-0.06	0.33	0.11	-0.17	0.02	0.38	1.00	
14. GDP growth rate	-0.12	0.17	0.11	0.07	0.29	0.03	-0.13	-0.01	0.10	-0.05	-0.18	0.27	0.56	1

Notes: This table reports the pairwise correlations between determinants of 'too-interconnected-to-fail' ranking of G-SIBs in Panel A and those of G-SIIs in Panel B. In panel A, the variables are: Log of inter-bank loans (IBL), Non-interest income/total interest income (NII), Trading account income/total interest income (TAI), Other non-interest income/total interest income (ONII), Tier1 leverage ratio (Tier1LR), Tier1 capital ratio (Tier1CR), (Tier 1 + Tier 2)/total asset (LR), Capital adequacy ratio (CR), Buckets of additional loss absorbency (ALA), Foreign sales/total sales (FS), Log of board size (BS), Total debt/total asset (L), Log of asset (A), Non-performing loans/total loans (NP), ROE (ROE), Coverage limit GDP per capita (DI), GDP growth rate (GDP), and BFCI Index (BFCI).

Table 3.10: Static Credit Risk Connectedness Table

VECM Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	From Others
1 ALLIANZ	7.6	5.6	5.3	5.1	2.9	2.2	1.5	1.5	4.7	3.2	4	3.9	4.4	4.4	2.5	3.7	2	4	3.6	3.5	3.8	1.1	2.6	3.1	2.4	2.7	2.7	2.2	2.7	0.1	0.1	0.8	92
2 ASSICURAZIONI GRLI	5.8	7.7	5.2	5	3.1	2.1	1.3	1.6	4.7	3	4	4	4.2	4.2	2.5	3.4	1.9	4.3	3.7	3.3	3.8	1	2.3	3.3	2.7	3	2.7	2.3	2.8	0.2	0.1	0.9	92
3 AVIVA	5.8	5.7	8.1	5.4	3.3	2.4	1.6	1.3	5.1	3.1	4	3.8	4.2	4.1	2.6	3.5	1.9	3.9	3.3	3.3	3.6	1	2.6	3.1	2.5	2.7	2.4	2.1	2.6	0.2	0.1	0.9	92
4 AXA	5.5	5.4	5.3	7.3	3.3	2.3	1.5	1.6	5.1	3	3.9	3.8	4.2	4.3	2.3	3.3	1.9	3.6	3.4	3.4	3.8	1.1	2.2	3.2	2.7	2.9	2.8	2.5	2.8	0.2	0.1	0.9	93
5 PRUDENTIAL	4.3	4.3	4.4	4.3	10.9	2.2	1.5	2.2	4.4	3.1	3.7	3.7	4.1	3.6	2.1	3	2.2	3.3	3.7	3.2	3.7	1.1	2.5	3.4	2.6	2.9	3	2.6	3	0.2	0.1	1.0	89
6 METLIFE	2.4	2.5	2.4	2.1	2	14.3	8.7	3.5	2.2	2.4	2.5	2.3	2.4	2.4	1.8	2.1	1.4	2	2	2.1	2.6	0.8	1.4	5.7	5.1	4.7	5.6	4.8	4.7	0.1	0.1	0.8	86
7 PRUDENTIAL FINANCL	2.2	2.1	2.1	1.8	1.6	11	14.5	3.5	1.9	2.3	2.6	2.3	2.1	2.3	1.8	2.1	1.3	1.8	2.1	1.8	2.4	1	1.5	5.6	5.2	4.9	5.6	4.9	4.5	0.2	0.1	0.9	86
8 AIG	2.5	2.8	2	2.3	2.6	4.1	3.3	17.3	2.2	2.3	2.5	2.4	2.5	2.5	1.2	1.9	1.3	1.8	2.3	1.7	2.6	1	0.8	4.8	5.6	5.9	5.7	5.6	5.4	0.2	0.0	0.9	83
9 AEGON	5.2	4.8	5	5.4	3.2	2.6	1.9	1.6	9.5	2.9	3.8	3.5	3.8	4.1	2.5	3	2	3	3.3	3.1	3.9	1	2.5	3.4	2.7	2.9	2.9	2.7	3	0.2	0.1	0.7	91
10 HSBC	3.7	3.5	3.3	3.3	2.3	1.9	1.4	1.7	3.1	8	5.2	4.6	4.7	4	3.3	3.7	2.6	4.8	4	3.8	3.9	1.2	3.4	3.2	2.8	3.1	2.9	2.5	2.9	0.3	0.1	1.0	92
11 BARCLAYS	3.7	3.5	3.3	3.1	2.1	1.7	1.2	1.4	3	4.2	8.1	4.9	4.9	4.4	3.6	4	2.5	4.9	4.1	4.1	4.4	1.4	3.2	3.2	2.8	3.2	2.9	2.5	3	0.1	0.0	0.7	92
12 BNP PARIBAS	3.9	3.8	3.6	3.3	2.3	1.4	1	1.3	3.1	3.8	5.2	7.9	4.7	4.6	2.8	4.7	2.5	5	5.4	3.9	4.7	1.2	2.9	2.9	2.5	2.8	2.8	2.3	2.5	0.1	0.0	0.9	92
13 DEUTSCHE BANK	4.1	4	3.7	3.4	2.5	1.7	1.1	1.5	3	3.7	4.9	4.5	8.2	4.7	3	3.9	2	4.5	3.9	4	5.1	1.4	2.7	3.3	2.8	3	3	2.5	2.8	0.2	0.1	0.9	92
14 CREDIT SUISSE	4.4	4.1	3.7	3.7	2.5	1.7	1.1	1.8	3.2	3.5	4.6	4.5	4.8	8.1	2.3	4.2	2.1	4.4	4.4	5.4	4	1.3	2.8	2.9	2.6	2.8	2.8	2.4	2.7	0.2	0.0	0.8	92
15 RBS	3.9	3.6	3.3	3.2	1.9	1.6	1.2	2	2.7	4.6	6.4	4.6	5.1	3.9	9.5	3.5	2.6	4.7	3.7	3.9	4.3	1.1	3.3	2.4	2.5	2.7	2.5	2.1	2.4	0.0	0.0	0.8	91
16 CREDIT AGRICOLE	3.8	3.5	3.4	3.1	2	1.4	1.1	1.3	3	3.5	4.9	5.7	4.6	4.7	2.6	7.9	2.7	5.3	5.6	4.1	4.1	1.3	3.3	3.1	2.7	2.8	2.7	2.4	2.5	0.1	0.0	0.9	92
17 ING BANK	3.7	3.3	3.4	3.3	2.3	1.6	1.3	1.6	3.3	4.2	5	4.5	4.3	3.9	3.2	4.2	8.4	4.9	4.3	4	3.9	1.2	3.9	2.7	2.4	2.9	2.5	2.4	2.6	0.1	0.0	0.8	92
18 SANTANDER	3.9	4.2	3.4	3.3	2	1.4	0.9	1.1	3.2	3.8	5.3	5	4.8	4.2	3	4.4	2.7	9.3	4.4	3.9	4.4	1	3.1	3.3	2.5	2.8	2.8	2.4	2.7	0.1	0.0	0.8	91
19 SOCIETE GENERALE	3.7	3.6	3.3	3.1	2.2	1.4	1.1	1.4	3.1	3.7	5	6.1	4.3	4.6	2.7	5.2	2.7	5.1	8.2	4	4.3	1.3	3.3	3	2.3	2.8	2.7	2.3	2.3	0.2	0.0	0.8	92
20 UBS	3.6	3.6	3.1	3.1	2.3	1.6	1.1	1.8	2.9	3.5	4.7	4.1	4.8	5.7	2.6	3.8	2.2	4.1	4	8.7	4	1	2.9	3.5	3.2	3.3	3.6	3.2	3.1	0.1	0.0	0.7	91
21 COMMERZBANK	4	4	3.6	3.7	2.6	1.6	1.1	1.5	3.4	3.6	4.9	4.9	5.6	4.4	2.8	3.9	2.4	4.7	4.3	3.9	8.2	1.4	2.7	3.1	2.4	2.8	2.6	2.3	2.7	0.2	0.0	0.9	92
22 DEXIA	3.3	2.9	2.7	3.2	2.3	1.3	0.8	2.1	2.4	3.1	4	4	4.1	4.1	2	3.3	1.8	3.4	4.7	3.9	3.8	16.1	2.1	2.8	2.5	2.9	2.8	2.9	2.9	0.6	0.1	0.9	84
23 LLOYDS	3.7	3.2	3.3	3	2	1.5	1.2	1.2	3.1	4.5	5.7	4.6	4.4	4.2	3.7	4.2	3.1	5.2	4.4	4.1	3.8	1	8.1	3	2.5	3.1	2.6	2.3	2.5	0.2	0.0	0.7	92
24 JPMORGAN CHASE	2.1	2.4	1.9	2	1.6	3	2.3	1.9	1.9	1.9	2.2	2.3	2.4	1.9	1.2	2.4	1.5	3	2.2	2	2.5	1	1.3	14	7.6	8.1	7.5	6.2	9.1	0.0	0.0	0.5	86
25 CITIGROUP	2	2.3	1.9	2	1.6	2.9	2.2	2.4	1.8	2.4	2.4	2.3	2.7	2	1.8	2.4	1.6	2.4	2.1	2.6	2.2	1	1.5	8	12	8.5	7.6	7	8	0.0	0.0	0.4	88
26 BANK OF AMERICA	1.9	2.2	1.7	1.8	1.4	2.7	2.3	2.4	1.6	2.1	2.3	2.3	2.4	1.8	1.4	2.4	1.6	2.5	2.2	2.2	2.2	1	1.6	9	8.6	13.2	7.6	6.4	8.8	0.0	0.0	0.3	87
27 GOLDMAN SACHS	2	2.2	1.6	1.8	1.6	3.1	2.5	3.5	1.6	2.4	2.5	2.3	2.7	2.2	1.4	2.4	1.6	2.4	2.2	2.4	2.2	1	1.4	7.6	7.5	7.3	11.7	9.2	7.1	0.0	0.0	0.5	88
28 MORGAN STANLEY	2	2.2	1.6	2	1.6	3.1	2.5	3.8	1.7	2.3	2.6	2.3	2.5	2.2	1.5	2.3	1.8	2.2	2.2	2.6	2.2	1.2	1.5	7	7.6	6.9	9.7	12	6.5	0.0	0.0	0.4	88
29 WELLS FARGO	1.8	2.1	1.6	1.7	1.4	2.7	2.2	2.2	1.5	1.6	2	2	2.1	1.7	1.2	2.2	1.4	2.5	1.9	1.8	2.1	1.3	1.2	10.4	8.8	9.3	8	6.8	13.9	0.0	0.0	0.4	86
30 MITSUBISHI	2.7	2.6	2.6	2.7	1.5	2.3	2	1.6	2.4	3.5	2.1	2.2	3.5	2.6	1	1.4	0.7	2.5	2.6	2.4	2.6	1.8	1.2	3	1.7	2.1	2.7	1.8	2.1	30.6	1.9	3.7	69
31 SUMITOMO MITSUI	2.7	2.5	2.5	2.5	2	2.5	1.9	1.2	2.3	2.8	2.7	2.7	2.8	2.2	1.6	1.5	1.3	2.1	2.4	2.2	2.5	0.9	1.5	3	2.1	2.7	2.9	2.3	2.6	2.0	31.0	2.1	69
32 BANK OF CHINA	3.1	3.5	2.9	3.1	2.2	2.3	1.7	1.6	2.5	3.3	3.4	4.1	3.8	3.2	2.9	3.1	2	3.4	3.6	2.6	3.8	1.5	2.1	3	2.4	2.8	3.3	2.4	2.8	1.1	0.4	16.3	84
Contribution to Others	108	106	97	97	68	75	56	59	90	97	119	114	118	109	71	99	61	111	106	99	107	36	71	129	114	121	122	107	116	7.0	4.0	28.0	2823
Net	16	14	5	4	-21	-11	-30	-24	-1	5	27	22	26	17	-20	7	-31	20	14	8	15	-48	-21	43	26	34	34	19	30	-62.0	-65.0	-56.0	**88.20%**

Table 3.10: Static Credit Risk Connectedness Table (Continued)

VAR model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	From Others
1 ALLIANZ	8.4	5.8	5.5	5.7	2.9	2	1.3	1.6	4.8	3.3	4.1	3.7	4.3	4.5	2.3	3.7	2.2	3.9	3.5	3.3	3.7	1.1	2.7	2.8	2.1	2.4	2.6	2.2	2.4	0.3	0.1	0.8	92
2 ASSICURAZIONI GRLI	6.1	8.6	5.5	5.5	3.1	1.8	1.3	1.6	4.8	3.1	4.1	3.8	4	4.2	2.3	3.5	2.2	4.1	3.6	3	3.8	1.1	2.5	2.9	2.3	2.6	2.6	2.2	2.5	0.3	0.1	0.9	91
3 AVIVA	6.1	5.7	8.9	5.7	3.3	1.9	1.4	1.4	5.1	3.1	4.1	3.6	4.1	4.2	2.4	3.6	2.2	3.9	3.1	3.2	3.6	1	2.8	2.7	2.3	2.4	2.3	2	2.4	0.3	0.1	0.9	91
4 AXA	5.8	5.6	5.4	8.5	3.3	2.1	1.5	1.6	5.4	3.2	4	3.4	4.2	4.3	2	3.5	2.1	3.7	3.4	3.3	3.8	1.2	2.5	2.7	2.2	2.6	2.6	2.3	2.5	0.4	0.1	0.9	92
5 PRUDENTIAL	4.3	4.4	4.5	4.4	12.9	2	1.5	2.3	4.4	3	3.4	3.5	3.8	3.6	1.9	3.1	2.4	3.1	3.4	3.1	3.4	1.3	2.5	3.1	2.4	2.7	2.7	2.4	2.7	0.5	0.2	1.1	87
6 METLIFE	2.5	2.4	2.2	2.2	1.9	16	9.3	3.6	2.4	2.4	2.4	2.3	2.3	2.3	1.7	2.2	1.4	1.7	1.9	2.1	2.4	1	1.3	5.3	4.7	4.6	5.4	4.7	4.4	0.2	0.1	0.9	84
7 PRUDENTIAL FINANCIAL	2.3	2.1	2.1	2.1	1.7	11.4	16.8	3.7	2.2	2.3	2.5	2.2	2.1	2.3	1.7	2.2	1.3	1.6	2	1.9	2.2	1.2	1.5	4.8	4.5	4.5	5	4.4	4	0.3	0.1	1	83
8 AIG	2.6	2.8	2.1	2.4	2.8	4	3.5	20.7	2.3	2.5	2.3	2.2	2.5	2.8	1.2	2.1	1.5	1.6	2.2	1.8	2.6	1.1	1.1	3.6	4.6	5.1	5.2	5.3	4.4	0.3	0.1	0.8	79
9 AEGON	5.5	4.9	5.1	5.9	3.2	2.6	1.9	1.7	10.7	3	3.8	3.3	3.9	4.2	2.2	3.2	2.2	3.1	3	3.1	3.7	1	2.5	2.8	2.2	2.6	2.5	2.4	2.5	0.3	0.1	0.9	89
10 HSBC	3.8	3.6	3.3	3.6	2.3	1.8	1.5	1.9	3.1	9.1	5.3	4.4	4.5	4	3.2	3.8	2.8	4.5	4	3.7	4.2	1.1	3.7	2.7	2.4	2.6	2.8	2.4	2.5	0.4	0.2	0.9	91
11 BARCLAYS	3.8	3.5	3.4	3.5	2.1	1.5	1.2	1.5	3.1	4.2	8.8	4.8	4.8	4.5	3.6	4.2	2.7	4.6	4.2	4.1	4.5	1.3	3.5	2.8	2.5	2.7	2.8	2.4	2.6	0.2	0.1	0.6	91
12 BNP PARIBAS	4	3.8	3.6	3.6	2.2	1.4	1.1	1.5	3.3	3.8	5.3	8.3	4.6	4.5	2.8	4.9	2.9	4.7	5.4	3.7	4.8	1.3	3.1	2.5	2.2	2.4	2.7	2.4	2.2	0.2	0.1	0.8	92
13 DEUTSCHE BANK	4.4	4	3.9	4	2.4	1.6	1.1	1.6	3.3	3.7	4.9	4.2	8.7	4.8	2.8	4	2.2	4.5	3.7	3.9	5.1	1.2	2.8	2.8	2.5	2.7	2.9	2.5	2.5	0.3	0.1	0.8	91
14 CREDIT SUISSE	4.6	4.1	3.9	4.1	2.5	1.4	1.1	1.7	3.5	3.6	4.7	4.3	4.9	9	2.2	4.2	2.4	4.4	4.3	5.3	4.2	1.1	3.1	2.4	2.2	2.5	2.6	2.2	2.2	0.3	0.1	0.8	91
15 RBS	3.9	3.6	3.5	3.2	1.8	1.5	1.1	2.1	2.8	4.5	6.4	4.5	4.9	3.5	11.4	3.5	2.8	4.4	3.5	3.8	4.3	1.2	3.5	2.1	2.3	2.4	2.5	2	2.2	0.1	0	0.8	89
16 CREDIT AGRICOLE	3.9	3.5	3.5	3.5	2	1.3	1.3	1.4	3	3.5	4.8	5.5	4.5	4.7	2.5	9.4	3.1	5	5.6	3.8	4.2	1.5	3.6	2.5	2.2	2.3	2.5	2.2	2.2	0.2	0	0.8	91
17 ING BANK	3.5	3.1	3.3	3.2	2.2	1.5	1.3	1.9	3.2	4.2	4.8	4.4	4	3.7	3.1	4.4	10.9	4.6	4.2	3.9	3.9	1.3	4.3	2.3	2.1	2.6	2.4	2.4	2.3	0.1	0.1	0.8	89
18 SANTANDER	4.1	4.2	3.8	3.6	2	1.1	0.9	1.2	3.2	3.8	5.4	4.7	4.7	4.4	2.8	4.5	3	10	4.5	3.6	4.6	0.8	3.5	2.8	2.3	2.5	2.7	2.2	2.4	0.2	0	0.8	90
19 SOCIETE GENERALE	3.7	3.6	3.2	3.3	2.2	1.3	1.2	1.5	3.1	3.7	4.9	6.1	4.2	4.5	2.5	5.7	3	4.8	9.3	3.8	4.5	1.4	3.6	2.6	2	2.5	2.5	2.2	2.1	0.2	0.1	0.7	91
20 UBS	3.8	3.6	3.4	3.5	2.4	1.4	1	1.9	3.2	3.5	4.7	4	4.6	5.8	2.6	4	2.4	3.9	3.8	9.5	4.1	1.1	3.2	2.9	2.8	2.9	3.3	3.1	2.7	0.2	0.1	0.6	90
21 COMMERZBANK	4.2	4.2	3.8	4.1	2.4	1.4	1	1.6	3.6	3.6	4.9	4.6	5.6	4.6	2.6	4	2.6	4.7	4.2	3.7	9.1	1.2	2.8	2.6	2.1	2.4	2.5	2.2	2.4	0.3	0.1	0.8	91
22 DEXIA	2.9	2.7	2.6	3.2	2.7	1.4	1.1	2.3	2.4	2.9	3.5	4	3.5	3.4	2.1	3.9	2.2	2.5	4.1	3.7	3.5	22	2.1	1.9	1.9	2.3	2.2	2.4	2.3	1	0.2	0.9	78
23 LLOYDS	3.6	3.1	3.3	3.1	2	1.2	1.2	1.3	3	4.6	5.6	4.7	4.1	4	3.7	4.5	3.5	5	4.5	3.9	4.1	1.1	9.9	2.5	2.1	2.6	2.4	2.1	2.2	0.2	0.1	0.7	90
24 JPMORGAN CHASE	2	2.2	1.7	1.7	1.6	2.7	2.2	1.7	1.6	1.7	2.2	2.1	2.2	1.7	1.1	2.1	1.2	2.7	2	1.6	2.2	0.9	1.1	15.5	8.1	8.3	8.5	7.3	9.5	0.1	0	0.4	84
25 CITIGROUP	1.9	2.1	1.8	1.8	1.7	2.7	2.2	2.2	1.6	2	2.3	2.1	2.5	1.9	1.7	2.1	1.4	2.1	1.8	2.2	1.9	0.9	1.3	8.3	13.4	8.9	8.5	8	8.3	0.1	0	0.4	87
26 BANK OF AMERICA	1.8	2	1.6	1.7	1.6	2.6	2.3	2.4	1.6	1.9	2.2	2.1	2.3	1.8	1.3	2.1	1.4	2.3	2	2	1.9	0.9	1.5	9	9	14	8.3	7.1	8.9	0.1	0.1	0.3	86
27 GOLDMAN SACHS	2	2	1.4	1.7	1.7	2.9	2.5	2.9	1.5	2.1	2.5	2.2	2.5	2	1.3	2.2	1.4	2.1	2	2.2	2	0.9	1.3	7.8	7.9	7.6	13.1	10.1	7.4	0.1	0.1	0.5	87
28 MORGAN STANLEY	1.9	2	1.5	1.8	1.7	2.9	2.4	3	1.5	2	2.5	2.2	2.3	2	1.5	2.2	1.6	1.9	2	2.5	1.9	1.2	1.4	7.1	7.9	7.1	10.7	13.9	6.8	0.1	0.1	0.4	86
29 WELLS FARGO	1.7	1.9	1.4	1.6	1.5	2.4	2.2	2.1	1.5	1.5	1.9	1.8	2	1.7	1.1	2	1.2	2.2	1.7	1.6	1.8	1.3	1.1	10.4	9	9.4	8.8	7.7	15	0	0.1	0.4	85
30 MITSUBISHI	2.4	2.6	2.4	2.4	2.2	2	1.9	1.5	2.1	3.1	2	1.9	2.7	2.5	1	1.5	1	2.2	2.3	2	2	1.7	1.3	2.9	1.6	2	2.3	1.5	1.9	36	1.9	3.4	64
31 SUMITOMO MITSUI	1.9	2.1	2.2	2	2.1	1.8	1.5	1.4	1.8	2.3	2.2	2.4	2.1	1.9	1.6	1.4	1.5	1.9	2	1.9	2.1	1	1.6	2	1.7	2.1	2	1.5	1.9	2	42.2	1.7	58
32 BANK OF CHINA	3.1	3.4	3	3.3	2.4	2.3	1.8	1.6	2.6	3.1	3.1	3.6	3.7	3.2	2.6	3.1	2	3.3	3.3	2.5	3.5	1.5	1.9	2.6	2.1	2.8	3	2.1	2.6	1.5	0.5	19.1	81
Contribution to Others	108	104	98	101	70	70	57	60	91	95	117	109	112	108	67	102	65	105	102	95	104	36	75	116	106	113	120	106	108	11	5	26	2761
Net	16	13	7	9	-17	-14	-26	-19	2	4	26	17	21	17	-22	11	-24	15	11	5	13	-42	-15	32	19	27	33	20	23	-53	-53	-55	**86.30%**

Notes: This table presents the static credit risk connectedness matrix among G-SIFIs from 2006 to 2014. The upper (lower) panel is based on the results of VECM (VAR) model. The ijth element of the upper left 32×32 submatrix indicates pairwise directional connectedness between firm i and j, with $i \neq j$. The column 'From others' depicts total directional connectedness of firm from all others, i.e., the sum of entries in the corresponding row. The row 'Contributions to others' illustrates total directional connectedness of firm to all others, i.e., the sum of entries in the corresponding column. The element in bottom-right corner is 'Total connectedness' of all firms, i.e., the average of 'From Others' connectedness, or equivalently, the average of 'Contributions to Others' connectedness. All the numbers in the upper left 32×32 submatrix, the numbers in the rows 'Contribution to Others' and 'Net', and those in the column 'From Others' are expressed in percentage (%).

Table 3.11: A Comparison of the 'Too-Interconnected-To-Fail' Ranking, Official G-SIBs List, and the 'Composite' Ranking

2013 'Too-Interconnected-To Fail' Ranking	2013 Official List of G-SIBs	2013 'Composite' Ranking
HSBC	**HSBC**	JP Morgan Chase
Crédit Agricole	**JP Morgan Chase**	HSBC
Barclays	**Barclays**	Citigroup
BNP Paribas	**BNP Paribas**	Deutsche Bank
Credit Suisse	**Citigroup**	BNP Paribas
Société Générale	**Deutsche Bank**	Barclays
Deutsche Bank	**Bank of America**	Bank of America
UBS	**Credit Suisse**	Credit Suisse
Morgan Stanley	**Goldman Sachs**	Morgan Stanley
Goldman Sachs	**Crédit Agricole**	Goldman Sachs
Citigroup	**Mitsubishi**	Mitsubishi
Santander	**Morgan Stanley**	RBS
JP Morgan Chase	**RBS**	Société Générale
RBS	**UBS**	Crédit Agricole
Bank of China	**Bank of China**	UBS
Bank of America	**ING**	Santander
ING	**Santander**	Bank of China
Wells Fargo	**Société Générale**	Wells Fargo
Sumitomo Mitsui	**Sumitomo Mitsui**	ING
Mitsubishi	**Wells Fargo**	Sumitomo Mitsui
2014 'Too-Interconnected-To Fail' Ranking	2014 Official List of G-SIBs	2014 Composite Ranking
Morgan Stanley	**HSBC**	JP Morgan Chase
JP Morgan Chase	**JP Morgan Chase**	HSBC
Goldman Sachs	**Barclays**	Citigroup
Citigroup	**BNP Paribas**	BNP Paribas
Wells Fargo	**Citigroup**	Deutsche Bank
Société Générale	**Deutsche Bank**	Barclays
Santander	**Bank of America**	Bank of America
Barclays	**Credit Suisse**	Credit Suisse
BNP Paribas	**Goldman Sachs**	Goldman Sachs
RBS	**Mitsubishi**	Mitsubishi
UBS	**Morgan Stanley**	Morgan Stanley
Deutsche Bank	**RBS**	RBS
HSBC	**Bank of China**	Société Générale
Crédit Agricole	**Crédit Agricole**	Santander
Credit Suisse	**ING**	Bank of China
Bank of America	**Santander**	Wells Fargo
ING	**Société Générale**	UBS
Bank of China	**Sumitomo Mitsui**	Crédit Agricole
Mitsubishi	**UBS**	Sumitomo Mitsui
Sumitomo Mitsui	**Wells Fargo**	ING

Notes: The first column is the 'too-interconnected-to fail' ranking proposed by this chapter. The second column is the official list of G-SIBs issued by the FSB. The red group represents that the banks should have 2.5% additional loss absorbency. According to the BCBS (2013), the higher loss absorbency requirement is associated with Common Equity Tier 1 capital as defined by the Basel III framework. The additional loss absorbency requirements for the members in the yellow group, the green group, and the blue group are 2.0 %, 1.5%, and 1.0%, respectively. The final column is the composite 'too-interconnected-to fail' ranking generated by combing the 'too-interconnected-to fail' ranking of this study and the official list provided by the FSB.

Table 3.12: Estimation Results of Determinants of the 'Too-Interconnected-To-Fail' Ranking (G-SIBs)

VECM model				
Log of inter-bank loans	5.659***	6.682***	5.430***	6.549***
	(0.001)	(0.001)	(0.003)	(0.000)
Non-interest income/total interest income	4.115*	4.600**	3.061	3.631
	(0.065)	(0.037)	(0.228)	(0.143)
Tier1 leverage ratio	-1.695**			
	(0.012)			
(Tier 1 + Tier 2 capital)/total assets		-1.002		
		(0.123)		
Tier1 capital ratio			0.026	
			(0.928)	
Capital adequacy ratio				0.107
				(0.738)
Extra loss absorbency requirements	1.728***	1.486***	1.325**	1.166*
	(0.005)	(0.008)	(0.045)	(0.085)
Foreign sales/total sales	0.085*	0.093**	0.055	0.070
	(0.087)	(0.044)	(0.247)	(0.142)
Log of board size	1.073	0.625	2.294*	0.553
	(0.530)	(0.723)	(0.098)	(0.753)
Total debt/total asset	0.146	0.152	0.152	0.171
	(0.213)	(0.225)	(0.294)	(0.227)
Log of assets	-8.256*	-9.058	-4.877	-6.090
	(0.085)	(0.131)	(0.340)	(0.266)
Non-performing loans/total loans	0.023	-0.158	-0.169	-0.036
	(0.959)	(0.736)	(0.713)	(0.933)
Return on Equity	0.012***	0.014**	0.008**	0.011**
	(0.001)	(0.011)	(0.042)	(0.035)
Coverage limit GDP per capita	-0.003	-0.004	-0.005	-0.004
	(0.795)	(0.757)	(0.646)	(0.757)
GDP growth rate	-0.212	-0.251	-0.342	-0.295
	(0.443)	(0.409)	(0.278)	(0.378)
BFCI Index	-1.035*	-1.052*	-0.640	-0.942*
	(0.054)	(0.076)	(0.183)	(0.071)
Constant	9.223	41.880	-26.946	9.869
	(0.827)	(0.405)	(0.579)	(0.833)
R-squared	44.95%	41.69%	33.86%	36.86%
No. of observations	113	111	111	113

Notes: This table reports the panel regression results of the equation (3.10) for G-SIBs:

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \tag{3.10}$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures based on the VECM model are used. $W_{i,t-1}$ is a vector of the proxies for interbank loans, non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ is a vector of variables, including global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. Hausman test suggests that GLS random-effect model is used to estimate the panel regression. Robust standard errors are used. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.12: Estimation Results of Determinants of the 'Too-Interconnected-To-Fail' Ranking (G-SIBs) (Continued)

VAR model				
Log of inter-bank loans	4.308*	5.949**	3.810	4.939*
	(0.085)	(0.026)	(0.160)	(0.063)
Non-interest income/total interest income	5.342***	6.441***	4.254*	4.534*
	(0.009)	(0.001)	(0.087)	(0.061)
Tier 1 leverage ratio	-1.479**			
	(0.024)			
(Tier 1 + Tier 2 capital)/total assets		-1.320**		
		(0.030)		
Tier 1 capital ratio			0.111	
			(0.713)	
Capital adequacy ratio				0.198
				(0.538)
Extra loss absorbency requirements	2.333***	2.158***	1.927**	1.780*
	(0.003)	(0.008)	(0.029)	(0.052)
Foreign sales/total sales	0.075**	0.104***	0.038	0.050
	(0.043)	(0.008)	(0.284)	(0.200)
Log of board size	0.883	0.548	1.330	0.440
	(0.630)	(0.763)	(0.501)	(0.806)
Total debt/total asset	0.080	0.094	0.060	0.072
	(0.460)	(0.421)	(0.608)	(0.550)
Log of assets	-6.338	-7.760	-4.628	-5.109
	(0.337)	(0.298)	(0.478)	(0.416)
Non-performing loans/total loans	-0.300	-0.448	-0.521	-0.392
	(0.526)	(0.289)	(0.236)	(0.359)
Return on Equity	0.010***	0.015**	0.007**	0.009**
	(0.002)	(0.013)	(0.021)	(0.022)
Coverage limit GDP per capita	-0.002	-0.003	-0.004	-0.003
	(0.869)	(0.817)	(0.724)	(0.770)
GDP growth rate	-0.285	-0.277	-0.374	-0.351
	(0.220)	(0.295)	(0.174)	(0.208)
BFCI Index	-1.285**	-1.381**	-1.014*	-1.176**
	(0.016)	(0.018)	(0.084)	(0.028)
Constant	2.276	36.723	-13.856	14.296
	(0.967)	(0.532)	(0.800)	(0.778)
R-squared	48.96%	49.13%	34.03%	39.05%
No. of observations	113	111	111	113

Notes: This table reports the panel regression results of the equation (3.10) for G-SIBs:

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \quad (3.10)$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures based on the VAR model are used. $W_{i,t-1}$ is a vector of the proxies for interbank loans, non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ is a vector of variables, including global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. Hausman test suggests that GLS random-effect model is used to estimate the panel regression. Robust standard errors are used to account for possible heteroskedatic residuals. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.13: Estimation Results of Determinants of the 'Too-Interconnected-To-Fail' Ranking (G-SIIs)

	VECM model	VECM model	VAR model	VAR model
Total liability/total insurance reserves	1.757	3.070	5.327**	7.208***
	(0.487)	(0.269)	(0.029)	(0.005)
Other income	0.126*	0.132	0.020	0.024
	(0.083)	(0.138)	(0.814)	(0.828)
Log of total assets	19.285**		24.527***	
	(0.027)		(0.000)	
Log of market capitalisation		5.943		8.829
		(0.259)		(0.116)
Foreign sales/total sales	0.121**	0.110*	0.107**	0.095*
	(0.021)	(0.059)	(0.024)	(0.073)
G-SII dummy	-2.252	-2.247	-3.490	-3.488
	(0.547)	(0.524)	(0.187)	(0.192)
Log of board size	-14.142	-13.742	-3.912	-3.727
	(0.363)	(0.421)	(0.741)	(0.780)
Loss ratio	-0.001	-0.026	0.008	-0.021
	(0.987)	(0.459)	(0.777)	(0.511)
Total debt/total asset	0.082	0.091	-0.065	-0.066
	(0.559)	(0.524)	(0.628)	(0.571)
Investment income/net revenue	1.295	-1.861	6.046**	2.409
	(0.749)	(0.609)	(0.021)	(0.404)
Operating expenses/total assets	19.037	19.235	58.546**	59.611**
	(0.606)	(0.624)	(0.043)	(0.045)
Return on Equity	0.089***	0.054*	0.064***	0.013
	(0.000)	(0.069)	(0.000)	(0.624)
BFCI Index	0.387	0.228	0.737	0.432
	(0.671)	(0.834)	(0.421)	(0.670)
GDP growth rate	-0.941*	-0.975	-0.522	-0.550
	(0.089)	(0.110)	(0.297)	(0.316)
Constant	-149.953*	-23.531	-219.736***	-69.260
	(0.068)	(0.608)	(0.000)	(0.137)
R-squared	32.15%	27.00%	39.73%	31.47%
No. of observations	75	75	75	75

Notes: This table reports the panel regression results of the equation (3.10) for G-SIIs:

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \tag{3.10}$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures based on the VECM or VAR model are used. $W_{i,t-1}$ is a vector of the proxies for NTNI activity and size. $Z_{i,t-1}$ is a vector of variables which consist of global activity, G-SII designation, corporate governance, insurance portfolio quality, leverage, investment activity, operating efficiency, GDP growth rate, management effectiveness, and financial condition indicator in one region in which a G-SII locates. As suggested by F-test, pooled OLS method is used. Also, robust standard errors are used. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.14: Additional Test I – Impact of Trading Account Income

VECM model				
Log of inter-bank loans	6.775***	7.547***	7.678***	8.225***
	(0.000)	(0.000)	(0.000)	(0.000)
Trading account income/total interest income	11.885**	11.889**	14.124**	11.642
	(0.025)	(0.033)	(0.050)	(0.126)
Tier 1 leverage ratio	-2.904***			
	(0.000)			
(Tier 1 + Tier 2 capital)/total assets		-1.679**		
		(0.033)		
Tier 1 capital ratio			-0.154	
			(0.707)	
Capital adequacy ratio				0.280
				(0.472)
Extra loss absorbency requirements	2.563***	1.971***	1.728***	1.194**
	(0.000)	(0.002)	(0.001)	(0.025)
Foreign sales/total sales	0.116**	0.103*	0.061	0.046
	(0.048)	(0.072)	(0.450)	(0.580)
Log of board size	0.709	-0.085	0.299	-0.376
	(0.702)	(0.966)	(0.863)	(0.839)
Total debt/total asset	0.174	0.159	0.259*	0.224
	(0.191)	(0.285)	(0.055)	(0.109)
Log of assets	-10.400	-10.654	-6.674	-6.019
	(0.100)	(0.210)	(0.354)	(0.437)
Non-performing loans/total loans	0.323	0.043	0.518	0.407
	(0.529)	(0.942)	(0.440)	(0.499)
Return on Equity	0.034**	0.037**	0.029*	0.033**
	(0.014)	(0.026)	(0.051)	(0.039)
Coverage limit GDP per capita	0.005	0.007	0.008	0.009
	(0.638)	(0.565)	(0.570)	(0.510)
GDP growth rate	-0.050	-0.225	-0.300	-0.365
	(0.889)	(0.562)	(0.475)	(0.385)
BFCI Index	-1.136*	-0.974	-1.132**	-0.970*
	(0.053)	(0.120)	(0.030)	(0.076)
Constant	56.349	54.448	5.218	-6.803
	(0.317)	(0.454)	(0.934)	(0.913)
R-squared	48.65%	44.24%	40.48%	40.81%
No. of observations	102	100	100	102

Notes: This table reports the panel regression results of the equation (3.10) for G-SIBs:

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \quad (3.10)$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures based on the VECM model are used. $W_{i,t-1}$ is a vector of the proxies for interbank loans, trading account income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ is a vector of variables, including global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. Hausman test suggests that GLS random-effect model is used to estimate the panel regression. Heteroskedasticity-robust standard errors are used. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.15: Additional Test II – Impact of Other Non-Interest Income

VECM model				
Log of inter-bank loans	6.625***	7.321***	8.218***	8.567***
	(0.000)	(0.004)	(0.001)	(0.001)
Other non-interest income/total interest income	4.179	4.091	4.643	4.999
	(0.112)	(0.126)	(0.213)	(0.106)
Tier 1 leverage ratio	-2.966***			
	(0.007)			
(Tier 1 + Tier 2 capital)/total assets		-1.633		
		(0.106)		
Tier 1 capital ratio			-0.032	
			(0.927)	
Capital adequacy ratio				0.251
				(0.464)
Extra loss absorbency requirements	2.245***	1.674**	1.560**	1.189*
	(0.002)	(0.021)	(0.023)	(0.066)
Foreign sales/total sales	0.200***	0.177**	0.110	0.095
	(0.009)	(0.025)	(0.295)	(0.377)
Log of board size	1.872	1.585	1.916	1.139
	(0.299)	(0.453)	(0.126)	(0.574)
Total debt/total asset	0.146	0.109	0.171	0.149
	(0.299)	(0.523)	(0.293)	(0.370)
Log of assets	-11.891*	-11.665	-9.452	-9.131
	(0.098)	(0.245)	(0.325)	(0.346)
Non-performing loans/total loans	0.464	0.224	0.430	0.318
	(0.454)	(0.726)	(0.580)	(0.647)
Return on Equity	0.030*	0.032*	0.030	0.033*
	(0.071)	(0.091)	(0.100)	(0.079)
Coverage limit GDP per capita	-0.005	-0.008	-0.009	-0.007
	(0.590)	(0.427)	(0.473)	(0.594)
GDP growth rate	0.050	0.094	0.223	0.201
	(0.861)	(0.759)	(0.524)	(0.554)
BFCI Index	-0.994	-0.892	-1.303**	-1.294**
	(0.140)	(0.201)	(0.043)	(0.042)
Constant	67.926	62.154	24.948	18.107
	(0.242)	(0.440)	(0.757)	(0.819)
R-squared	47.63%	43.70%	42.35%	42.12%
No. of observations	88	86	87	88

Notes: This table reports the panel regression results of the equation (3.10) for G-SIBs:

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \quad (3.10)$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures based on the VECM model are used. $W_{i,t-1}$ is a vector of the proxies for interbank loans, other non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ is a vector of variables, including global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. Hausman test suggests using GLS random-effect model. Heteroskedasticity-robust standard errors are used. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.16: Robustness Test I – GMM Estimation Method

Panel A: GMM regressions of G-SIBs (VECM)				
Log of inter-bank loans	6.479***	7.194***	7.405***	7.493***
	(0.000)	(0.000)	(0.000)	(0.000)
Non-interest income/total interest income	6.774***	7.284***	7.947***	7.304***
	(0.002)	(0.001)	(0.001)	(0.002)
Tier 1 leverage ratio	-2.408***			
	(0.000)			
(Tier 1 + Tier 2 capital)/total assets		-1.471***		
		(0.001)		
Tier 1 capital ratio			-0.241	
			(0.374)	
Capital adequacy ratio				0.012
				(0.966)
Extra loss absorbency requirements	1.860**	1.401*	1.299	0.968
	(0.019)	(0.069)	(0.121)	(0.250)
Foreign sales/total sales	0.143***	0.139***	0.141***	0.134***
	(0.000)	(0.001)	(0.002)	(0.005)
Log of board size	0.869	0.320	1.262	0.481
	(0.508)	(0.814)	(0.425)	(0.740)
Total debt/total asset	0.276***	0.267***	0.366***	0.336***
	(0.001)	(0.002)	(0.000)	(0.000)
Log of assets	-6.228	-6.690	-2.773	-2.454
	(0.250)	(0.253)	(0.638)	(0.670)
Non-performing loans/total loans	0.145	-0.139	0.172	0.115
	(0.774)	(0.781)	(0.734)	(0.816)
Return on Equity	0.023***	0.025***	0.015**	0.018***
	(0.003)	(0.002)	(0.025)	(0.006)
Coverage limit GDP per capita	-0.001	0.000	-0.001	0.000
	(0.896)	(0.983)	(0.885)	(0.955)
GDP growth rate	-0.056	-0.179	-0.270	-0.295
	(0.851)	(0.558)	(0.408)	(0.360)
BFCI Index	-1.443**	-1.317**	-1.394*	-1.316*
	(0.024)	(0.048)	(0.055)	(0.057)
Constant	12.775	12.702	-35.986	-38.655
	(0.799)	(0.812)	(0.503)	(0.454)

Panel B: GMM regressions of G-SIIs (VECM)		
Total liability/total insurance reserves	1.757	3.070
	(0.438)	(0.216)
Other income	0.126*	0.132*
	(0.051)	(0.095)
Log of total assets	19.285**	
	(0.012)	
Log of market capitalisation		5.943
		(0.206)
Foreign sales/total sales	0.121***	0.110**
	(0.008)	(0.033)
G-SII dummy	-2.252	-2.247
	(0.502)	(0.478)
Log of board size	-14.142	-13.742
	(0.309)	(0.369)
Loss ratio	-0.001	-0.026
	(0.986)	(0.409)

Total debt/total asset	0.082	0.091
	(0.514)	(0.478)
Investment income/net revenue	1.295	-1.861
	(0.722)	(0.569)
Operating expenses/total assets	19.037	19.235
	(0.565)	(0.585)
Return on Equity	0.089***	0.054**
	(0.000)	(0.040)
BFCI Index	0.387	0.228
	(0.636)	(0.816)
GDP growth rate	-0.941*	-0.975*
	(0.055)	(0.072)
Constant	-149.953**	-23.531
	(0.040)	(0.568)

Notes: This table reports the GMM estimation results of the equation (3.10).

$$ranking_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t} \tag{3.10}$$

where $ranking_{i,t}$ is the ranking of the ith financial institution at year t when the connectedness measures are obtained from VECM model. For G-SIBs, $W_{i,t-1}$ include interbank loans, non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ include global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. For G-SIIs, $W_{i,t-1}$ include NTNI activity and size. $Z_{i,t-1}$ include global activity, G-SII designation, corporate governance, insurance portfolio quality, leverage, investment activity, operating efficiency, management effectiveness, GDP growth rate, and financial condition indicator in one region in which a G-SII locates. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.17: Robustness Test II – Ordered Logit/Probit Model

VECM model for G-SIBs	Ordinal Logit	Ordinal Logit	Ordinal Logit	Ordinal Logit
Log of inter-bank loans	1.937***	2.006***	1.912***	2.190***
	(0.001)	(0.000)	(0.000)	(0.001)
Non-interest income/total interest income	0.841	0.849	1.216*	1.148*
	(0.284)	(0.214)	(0.066)	(0.096)
Tier1 capital ratio	-0.054			
	(0.512)			
Capital adequacy ratio		-0.009		
		(0.906)		
Tier1 leverage ratio			-0.577***	
			(0.001)	
(Tier 1 + Tier 2 capital)/total assets				-0.261
				(0.234)
Extra loss absorbency requirements	0.341*	0.279	0.410**	0.343**
	(0.096)	(0.170)	(0.037)	(0.030)
Foreign sales/total sales	0.020*	0.020	0.029***	0.026**
	(0.093)	(0.101)	(0.007)	(0.019)
Log of board size	0.584	0.118	0.176	0.105
	(0.179)	(0.827)	(0.729)	(0.846)
Total debt/total asset	0.067*	0.057	0.059*	0.049
	(0.075)	(0.117)	(0.058)	(0.174)
Log of assets	-1.153	-1.817	-1.994	-2.777
	(0.401)	(0.207)	(0.110)	(0.119)
Non-performing loans/total loans	0.013	0.028	0.059	-0.011
	(0.914)	(0.829)	(0.629)	(0.932)
Return on Equity	0.001	0.002	0.003*	0.003
	(0.163)	(0.155)	(0.086)	(0.131)
Coverage limit GDP per capita	-0.002	-0.001	-0.001	-0.001
	(0.615)	(0.653)	(0.732)	(0.658)
GDP growth rate	-0.125	-0.096	-0.068	-0.087
	(0.235)	(0.365)	(0.482)	(0.385)
BFCI Index	-0.187	-0.268*	-0.301*	-0.307*
	(0.232)	(0.059)	(0.071)	(0.079)

Notes: This table reports the estimation results of random-effects ordered Logit model for G-SIBs. The ordered Logit model is defined as:

$$y_{i,t}^{*} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t}$$

$$y_{i,t} = \begin{cases} 1, \ if & y_{i,t}^{*} \leq \kappa_1 \\ 2, \ if & \kappa_1 < y_{i,t}^{*} \leq \kappa_2 \\ \vdots & \\ N, \ if & \kappa_{N-1} < y_{i,t}^{*} \end{cases}$$

where $y_{i,t}^{*}$ is an unobserved latent variable linked to the observed ordinal response categories $y_{i,t}$ which is the ranking of the ith financial institution at year t when the connectedness measures are obtained from VECM model. κ represents cutpoints to be estimated (along with the γ_0, γ, and ξ coefficients) using maximum likelihood estimation, subject to the constraint that $\kappa_1 < \kappa_2 \cdots < \kappa_{N-1}$. N is the largest value of $y_{i,t}$. In this study, $N = 32$. For G-SIBs, $W_{i,t-1}$ include interbank loans, non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ include global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.17: Robustness Test II – Ordered Logit/Probit Model (Continued)

VECM model for G-SIBs	Ordinal Probit	Ordinal Probit	Ordinal Probit	Ordinal Probit
Log of inter-bank loans	1.008***	1.123***	1.077***	1.225***
	(0.002)	(0.001)	(0.000)	(0.001)
Non-interest income/total interest income	0.420	0.456	0.724*	0.720*
	(0.341)	(0.241)	(0.055)	(0.087)
Tier1 capital ratio	-0.018			
	(0.734)			
Capital adequacy ratio		0.005		
		(0.909)		
Tier1 leverage ratio			-0.342***	
			(0.001)	
(Tier 1 + Tier 2 capital)/total assets				-0.175
				(0.159)
Extra loss absorbency requirements	0.221*	0.187	0.270**	0.225**
	(0.090)	(0.144)	(0.021)	(0.023)
Foreign sales/total sales	0.011	0.011*	0.018***	0.017***
	(0.111)	(0.092)	(0.003)	(0.007)
Log of board size	0.225	-0.047	0.002	-0.060
	(0.377)	(0.869)	(0.993)	(0.838)
Total debt/total asset	0.032	0.029	0.033**	0.028
	(0.141)	(0.163)	(0.042)	(0.152)
Log of assets	-0.763	-1.107	-1.226*	-1.581
	(0.366)	(0.182)	(0.084)	(0.106)
Non-performing loans/total loans	-0.003	0.003	0.027	-0.016
	(0.965)	(0.962)	(0.680)	(0.812)
Return on Equity	0.001	0.001*	0.002*	0.002
	(0.100)	(0.072)	(0.058)	(0.136)
Coverage limit GDP per capita	0.000	0.000	0.000	0.000
	(0.876)	(0.910)	(0.997)	(0.935)
GDP growth rate	-0.053	-0.042	-0.025	-0.038
	(0.339)	(0.445)	(0.598)	(0.465)
BFCI Index	-0.148*	-0.189**	-0.218**	-0.214**
	(0.099)	(0.021)	(0.020)	(0.031)

Notes: This table reports the estimation results of random-effects ordered Probit model for G-SIBs. The ordered Probit model is defined as:

$$y^*_{i,t} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t}$$

$$y_{i,t} = \begin{cases} 1, \ if & y^*_{i,t} \leq \kappa_1 \\ 2, \ if & \kappa_1 < y^*_{i,t} \leq \kappa_2 \\ \vdots & \\ N, \ if & \kappa_{N-1} < y^*_{i,t} \end{cases}$$

where $y^*_{i,t}$ is an unobserved latent variable linked to the observed ordinal response categories $y_{i,t}$ which is the ranking of the ith financial institution at year t when the connectedness measures are obtained from VECM model. κ represents cutpoints to be estimated (along with the γ_0, γ, and ξ coefficients) using maximum likelihood estimation, subject to the constraint that $\kappa_1 < \kappa_2 \cdots < \kappa_{N-1}$. N is the largest value of $y_{i,t}$. In this study, $N = 32$. For G-SIBs, $W_{i,t-1}$ include interbank loans, non-interest income, regulatory capital ratio, and additional loss absorbency bucket. $Z_{i,t-1}$ include global activity, corporate governance, leverage, size, credit risk, management effectiveness, deposit insurance policy, GDP growth rate, and financial condition indicator in one region in which a G-SIB locates. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 3.17: Robustness Test II – Ordered Logit/Probit Model (Continued)

VECM model for G-SIIs	Ordinal Probit	Ordinal Logit	Ordinal Probit	Ordinal Logit
Total liability/total insurance	0.224	0.416	0.369	0.646
reserves	(0.536)	(0.509)	(0.398)	(0.211)
Other income	0.022**	0.042**	0.023	0.042*
	(0.033)	(0.023)	(0.201)	(0.061)
Log of total assets	3.022***	5.063**		
	(0.007)	(0.015)		
Log of market capitalisation			0.663	1.145
			(0.682)	(0.226)
Foreign sales/total sales	0.019**	0.035**	0.016**	0.031*
	(0.014)	(0.015)	(0.040)	(0.065)
G-SII dummy	-0.309	-0.792	-0.267	-0.554
	(0.494)	(0.309)	(0.666)	(0.492)
Log of board size	-1.842	-2.492	-1.320	-2.307
	(0.508)	(0.633)	(0.842)	(0.624)
Loss ratio	-0.002	-0.003	-0.005	-0.011
	(0.689)	(0.629)	(0.602)	(0.203)
Total debt/total asset	0.002	-0.002	0.003	0.003
	(0.904)	(0.935)	(0.821)	(0.908)
Investment income/net revenue	-0.007	-0.125	-0.535	-1.110
	(0.990)	(0.910)	(0.358)	(0.193)
Operating expenses/total assets	2.269	2.887	1.288	1.472
	(0.648)	(0.749)	(0.926)	(0.879)
Return on Equity	0.013***	0.022***	0.008	0.015*
	(0.000)	(0.000)	(0.172)	(0.071)
BFCI Index	0.101	0.194	0.087	0.158
	(0.375)	(0.339)	(0.475)	(0.495)
GDP growth rate	-0.139*	-0.269**	-0.141	-0.262*
	(0.076)	(0.025)	(0.104)	(0.051)

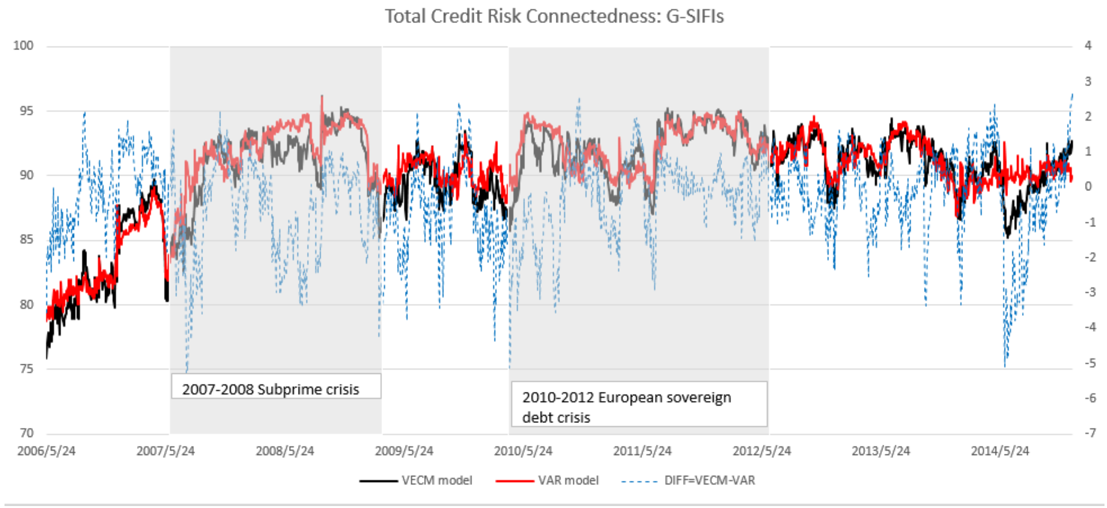
Notes: This table reports the estimation results of random-effects ordered Logit/Probit model for G-SIIs. The ordered Logit/Probit model is defined as:

$$y_{i,t}^{*} = \gamma_0 + \gamma W_{i,t-1} + \xi Z_{i,t-1} + \varepsilon_{i,t}$$

$$y_{i,t} = \begin{cases} 1,\ if & y_{i,t}^{*} \leq \kappa_1 \\ 2,\ if & \kappa_1 < y_{i,t}^{*} \leq \kappa_2 \\ \vdots & \\ N,\ if & \kappa_{N-1} < y_{i,t}^{*} \end{cases}$$

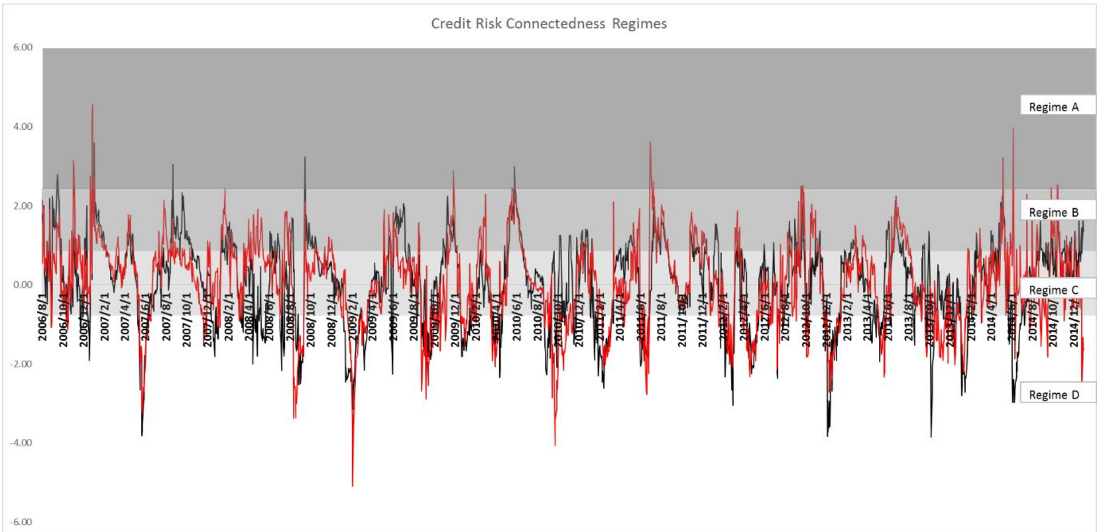
where $y_{i,t}^{*}$ is an unobserved latent variable linked to the observed ordinal response categories $y_{i,t}$ which is the ranking of the ith financial institution at year t when the connectedness measures are obtained from VECM model. κ represents cutpoints to be estimated (along with the γ_0, γ, and ξ coefficients) using maximum likelihood estimation, subject to the constraint that $\kappa_1 < \kappa_2 \cdots < \kappa_{N-1}$. N is the largest value of $y_{i,t}$. In this study, $N = 32$. For G-SIIs, $W_{i,t-1}$ include NTNI activity and size. $Z_{i,t-1}$ include global activity, G-SII designation, corporate governance, insurance portfolio quality, leverage, investment activity, operating efficiency, management effectiveness, GDP growth rate, and financial condition indicator in one region in which a G-SII locates. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Figure 3.1: Total Credit Risk Connectedness of G-SIFIs



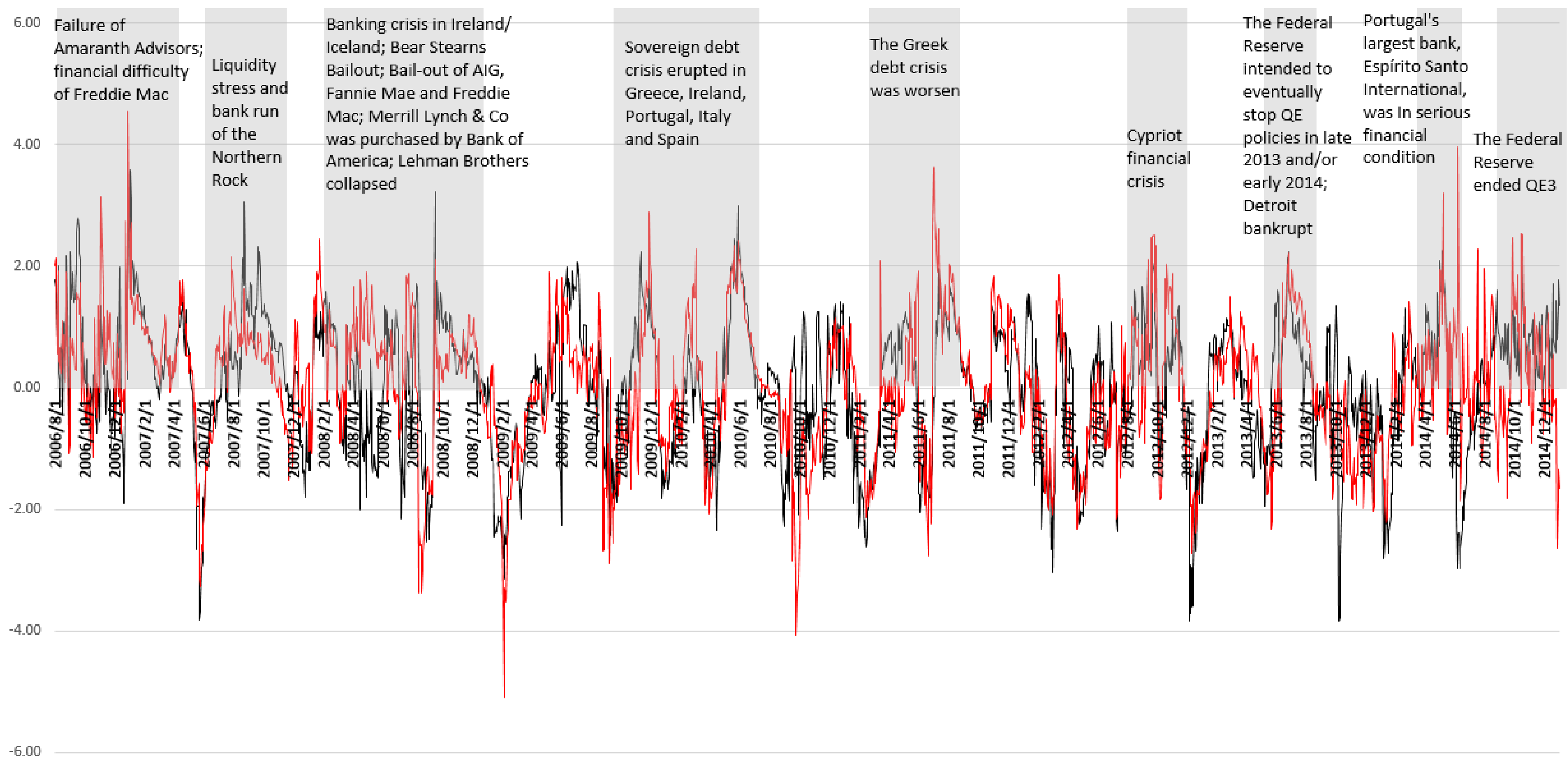
Notes: This figure depicts the total credit risk connectedness of G-SIFIs. Black (red) line is total credit risk connectedness of G-SIFIs based on VECM (VAR) model. The blue line represents the difference between (VECM-VAR) two time series. The values of connectedness are expressed in percentage (%).

Figure 3.2: Scored Credit Risk Connectedness (Z_{CRC}) and Connectedness Regimes



Notes: This figure presents the scored credit risk connectedness and four connectedness regimes. Black line is Z_{CRC} based on VECM model and red line is Z_{CRC} based on VAR model.

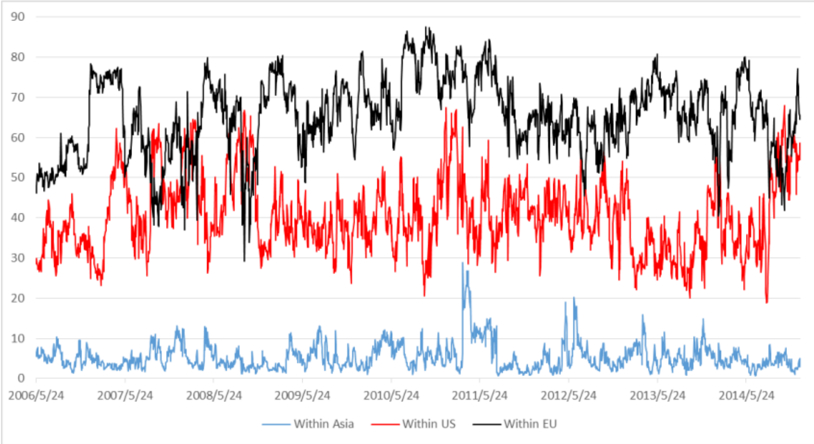
Figure 3.3: Z_{CRC} and Financial Crisis Periods



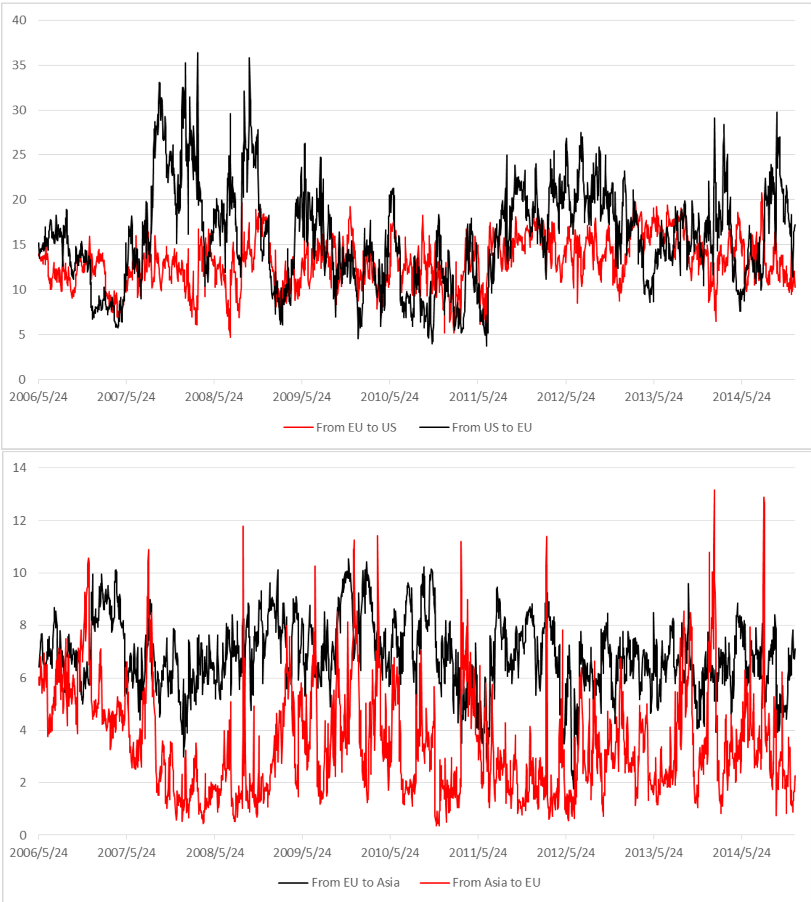
Notes: This figure indicates the scored credit risk connectedness, Z_{CRC}, and several critical events during the financial catastrophes. The chronology of severe financial events is selected by referencing 'Full Timeline' of the Federal Reserve Bank of St. Louis, Louzis and Vouldis (2013), and financial news. Black line is Z_{CRC} based on VECM model and red line is Z_{CRC} based on VAR model.

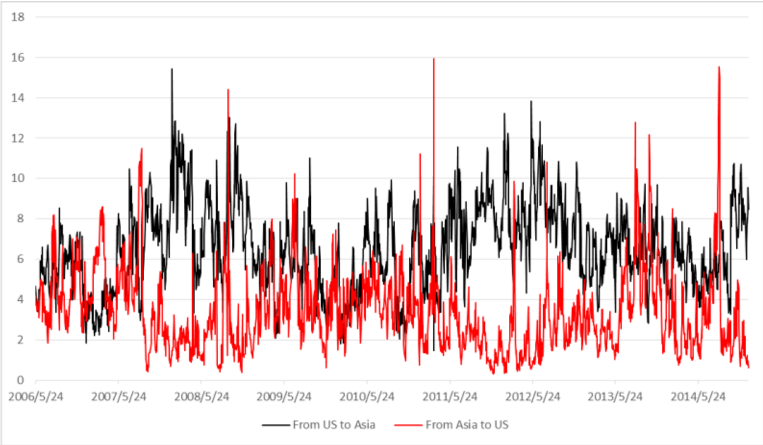
Figure 3.4: Total Directional Connectedness: Cross-Region and Within-Region

Panel A: Credit Risk Connectedness Originating from One Region



Panel B: Credit Risk Connectedness Cross Any Two Regions

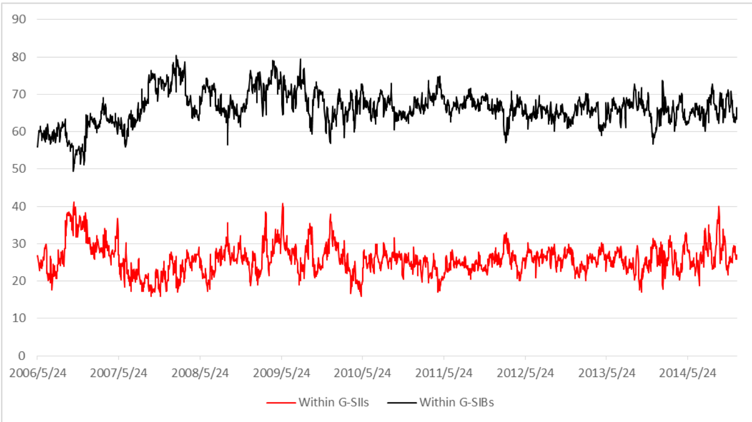




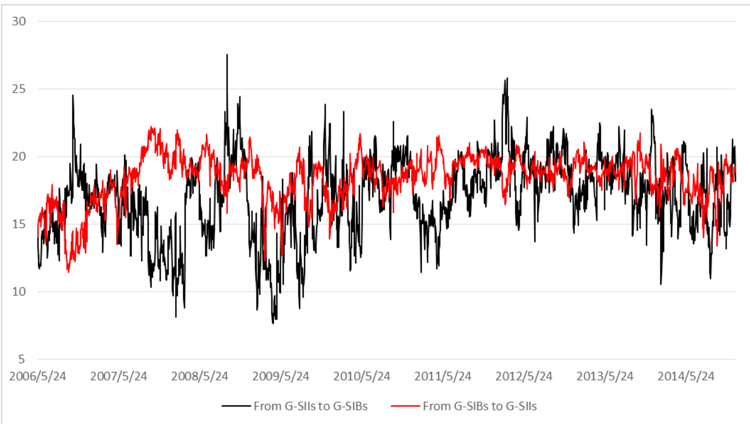
Notes: This figure depicts the total directional connectedness: cross-region in Panel A and within-region in Panel B. The values of connectedness are expressed in percentage (%).

Figure 3.5: Total Directional Connectedness: Cross-Group and Within-Group

Panel A: Credit Risk Connectedness Originating from One Group



Panel B: Credit Risk Connectedness Cross Any Two Groups



Notes: This figure depicts the total directional connectedness: cross-group in Panel A and within-group in Panel B. The values of connectedness are expressed in percentage (%).

Appendix 3A: Cross-Region/Group and Within-Region/Group Connectedness

Suppose there are N firms and M regions or groups. In the ith region/group, there are p_i firms. So, $\sum_{i=1}^{M} p_i = N$. The total number of pairwise connectedness series is $N^2 - N$. The number of within-region pairwise connectedness series in the ith region is $p_i(p_i - 1)$; therefore, the total number of within-region pairwise connectedness series is $\sum_{i=1}^{M} p_i(p_i - 1)$. The number of cross-region pairwise connectedness series between the ith region and the jth region is $2p_ip_j$, $i \neq j$. Among these $2p_ip_j$ series, half of them are pairwise connectedness from the ith region to the jth region and the other half of the series are pairwise connectedness from the jth region to the ith region. The total number of cross-region pairwise connectedness series is $\sum_{i,j=1,i\neq j}^{M} 2p_ip_j = N^2 - N - \sum_{i=1}^{M} p_i(p_i - 1)$.

Total connectedness of N firms is calculated by summing $N^2 - N$ series of pairwise connectedness and dividing the sum by N. Following the same procedure, total connectedness within the ith region/group is calculated by summing ${p_i}^2 - p_i$ series of pairwise connectedness and divide the sum by p_i. Total directional connectedness from the ith region to the jth region is calculated by summing the corresponding p_ip_j series of pairwise connectedness and dividing the sum by $(p_i + p_j)$. Total directional connectedness from the jth region to the ith region is calculated by summing the corresponding p_ip_j pairwise connectedness series and dividing the sum by $(p_i + p_j)$.

Chapter 4: Impact of Sovereign Credit Rating and Bailout Events on Sovereign CDS and Equity Index: Evidence from the U.S., the U.K., and the Eurozone States

4.1 Introduction

Prior to the European sovereign debt crisis, sovereign credit risk of emerging economies was the major concern of academics, policymakers, and investors. However, during the past decade, sovereign default risk of developed countries has become undoubtedly important. Therefore, this chapter is motivated to focus on sovereign default risk of major advanced economies, i.e., the U.S., the U.K., and the Eurozone states. A number of researchers have examined the relationship between sovereign CDS and government bond, such as IMF (2013) and Fontana and Scheicher (2016). Nevertheless, only a few studies investigate the relationship between sovereign CDS and equity index. Sovereign CDS and equity markets are both related to one country's probability of default (Ngene et al., 2014). Since sovereign CDS contract provides investors with protection to against contingent default of one country, sovereign CDS spread is directly depend on country credit risk. Equity market and sovereign default risk are linked through macroeconomic fundamentals (Jeanneret, 2017), corporate borrowing costs (Bedendo and Colla, 2015), and global investors' trading decisions (Hooper et al., 2008). This chapter studies the relation of these two assets from the perspective of their time-varying contemporaneous correlation. Asset correlation is critically important for policymakers to monitor risk transmission across markets and for global investors to manage portfolios and control risk (e.g., Karolyi and Stulz, 1996; Fleming et al., 1998).

The impact of sovereign credit risk events on sovereign CDS and equity index has been separately examined by previous studies, such as Afonso et al. (2012) and Hooper et al. (2008). However, the question of whether the relationship between the two assets in a country is affected by sovereign credit risk news has not been answered. As suggested by Andersen et al. (2007), it is also important to approach the central question of price discovery by studying the news impact on returns and volatility of different assets as well as the linkages across assets. Thus, we aim at extending the current understanding of the news impact on sovereign CDS and equity index by examining the news impact not only on their returns and volatility, but also on their correlation. The correlation of assets may change at the arrival of macro news, which can be attributable to any cross-asset trading caused by information spillovers, portfolio rebalancing, wealth effects, and increased dispersion of investors' forecasts (Brenner et al., 2009). Accordingly, it can be expected that macro events conveying tradable news about one country's default risk are likely to affect the correlation of sovereign CDS and equity index. We consider sovereign credit rating events and bailout events of troubled financial firms or distressed Eurozone states. To obtain a more general measure of sovereign credit rating events, we aggregate three major rating agencies' rating information, which complements the method of Gande and Parsley (2005). Unlike Drago and Gallo (2016) who use dummy variable to account for anticipation effects of outlooks/watchlists, we calculate rating surprises which quantify the unexpected component of actual rating actions.

While a stream of literature has studied the spillover effect of sovereign rating events across countries and assets, e.g., Ferreira and Gama (2007) and Arezki et al. (2011), limited papers have examined the spillover effect of a country's sovereign rating news on the relationship between sovereign CDS and equity index in other economies. Hence, this chapter aims to fill in this gap. According to Ismailescu and Kazemi (2010), besides similar economic fundamentals, transmission channels of a country's sovereign credit rating news include international trade, common creditor, competition in a third market, membership in a trade bloc, and regional proximity. Due to the crucial role of Greece in the European sovereign debt crisis, this chapter studies the spillover effect of Greek sovereign rating news. Given that the U.S., the U.K., and the Eurozone states are closely linked by global trades and/or geographic proximity, Greek sovereign rating events are likely to produce spillover effect.

In sum, using an asymmetric dynamic conditional correlation model with exogenous variables (ADCC-X), we simultaneously study the impact of sovereign credit risk news on the returns, volatility, and correlation of sovereign CDS and equity index in major advanced economies. This allows us to tackle two research questions.

a) How do sovereign default risk events affect the returns and volatility of sovereign CDS and equity index?
b) How do sovereign default risk events affect the correlation between sovereign CDS and equity index?

The major findings are briefly summarised as follows. First, domestic rating events and rating surprises have more significant impact on sovereign CDS than on equity index. Rating events or surprises are accompanied by a lower degree of asset correlation. Domestic good and bad rating events present both asymmetric and symmetric impact on the returns and volatility of two assets. For the correlation, symmetric impact of two rating news is found in Spain, Italy, and Cyprus, whereas asymmetric impact is detected in Portugal, Ireland, Netherlands, Finland, and the United States. On the announcement days of major bailouts, sovereign CDS spreads widen and equity index prices fall. Asset volatility increases, and two assets become more negatively correlated. Compared with domestic sovereign rating events, bailout events present more pronounced influence on assets. Finally, Greek rating news generates spillover effect and generally has a positive impact on the correlation of sovereign CDS and equity index in the sample countries.

This chapter contributes to the existing literature in several aspects. First, it adopts a more general measure to define sovereign credit rating events, which incorporates the information released by the three main rating agencies. It also calculates rating surprises, which quantify the size of the unexpected component of actual rating actions. These complement the approaches of Gande and Parsley (2005) and Drago and Gallo (2016). Second, using the ADCC-X model, this study extends the existing understanding of the news impact on sovereign CDS and equity index in terms of the returns, volatility, and correlation. Consistent with Andersen et al. (2007) and Brenner et al. (2009), we find that the asset correlation can be explained by the releases of sovereign credit rating and bailout news. Bailout news has more significant impact. Finally, it adds to the existing literature associated with the spillover effect of sovereign rating events, e.g., Ismailescu and Kazemi (2010) and Afonso et al. (2012), by showing that in several sample states, Greek rating news can affect the returns, volatility, and correlation of the two assets.

The rest of this chapter is organized as follows. Section 4.2 reviews related literature and develops hypotheses. Section 4.3 describes the methods to define rating events, rating surprises, and bailout events, and also presents the ADCC-X model. Section 4.4 reports the data. Section 4.5 presents the empirical results and Section 4.6 concludes.

4.2 Related Literature and Hypothesis Development

4.2.1 Relationship between Sovereign CDS and Equity Index

The general reason why sovereign CDS and equity markets are interrelated is that they are both associated with sovereign default risk (Ngene et al., 2014). On the one hand, sovereign CDS contract offers investors an insurance to against contingent sovereign default; therefore, sovereign CDS spread is directly determined by country default risk. On the other hand, equity market and sovereign default risk are linked by economic fundamentals (Jeanneret, 2017), corporate borrowing costs (Bedendo and Colla, 2015), and global investors' trading decisions (Hooper et al., 2008). To be specific, Jeanneret (2017) suggests that sovereign credit risk and equity market jointly react to common economic shocks regarding corporate revenues. Also, increased sovereign default risk would decrease the market values of government bonds held by financial institutions. The losses would reduce these firms' credit supply for the economy and consequently adversely influence the whole equity market. Bedendo and Colla (2015) argue that a distressed government may transfer its debt burden to the corporate sector by increasing taxation, intervening foreign exchange, or regulating private investment. As a result, corporate borrowing costs would increase and, eventually, the national equity market is adversely affected. In addition, sovereign default risk is an important input for global investors to manage portfolios. Thus, variations of sovereign default risk may induce portfolio rebalancing activities and then affect equity market (Hooper et al., 2008).

The relationship between sovereign CDS and equity index can be inferred by structural credit risk pricing theory, price discovery, and arbitrage/hedge activity. First, Merton's (1974) model in which the probability of default of one firm can be calculated by using equity market information is also applicable for sovereign debt and equity index. Chan-Lau and Kim (2004) argue that the only considerable difference between a corporation and a sovereign issuer with the equal amount of debt is that default risk is higher for the sovereign for every asset value because the sovereign can choose to default even if it is technically solvent. This choice is referred to as 'willingness-to-pay'. They heuristically justify that this choice does not affect the possible relation between sovereign debt and equity index implied by Merton's model. Adopting an extended Black-Scholes-Merton option pricing model, Oshiro and Saruwatari (2005) present that one country's default probability can be derived from its equity index price. Given that sovereign CDS is written on sovereign debt and provides an insurance to against contingent default on the underlying sovereign obligation, its interrelationship with equity index can also be implied by Merton's theory (Chan-Lau and Kim, 2004).

Also, price discovery relation between the two assets has been empirically studied. Both sovereign CDS spreads and equity index prices are related to one country's default risk. However, due to the differences in market structures, investors, and trading constraints, these two assets are more likely to react to sovereign credit risk news at different speeds. Chan et al. (2009) show that in seven Asian countries, sovereign CDS responds to country default risk news more rapidly than equity index, because the sovereign CDS market has fewer constraints, more sophisticated investors, and greater informational advantage than the undeveloped equity market. However, in eight European countries, Coronado et al. (2012) document that stock index leads sovereign CDS from 2007 to 2009. In thirteen emerging markets, Ngene et al. (2014) find a nonlinear price discovery relation of the two assets and identify two regimes. Sovereign CDS leads equity index in the lower regime, while their lead-lag relation is ambiguous in the upper regime.

Moreover, Chan et al. (2009) and Ngene et al. (2014) suggest that the capital structure arbitrage elaborated by Yu (2006) is also applicable for sovereign CDS and equity index. Capital structure arbitrageurs earn risk-free profits from the discrepancies between the observed CDS spread and the theoretical spread extracted from a Merton-type structural model (Chan et al., 2009). When the market spread is considerably larger (smaller) than the implied spread, arbitrageurs can short (long) default insurance, short (long) equity index, or do both. The investment decisions made by arbitrageurs depend on their belief about which market would be correct. Ngene et al. (2014) argue that hedging activities exist between these two assets. When a country's default risk increases, equity market may be adversely affected. It is ascribed to either the deteriorating economic condition or the higher risk premium required by worldwide investors. The demand for sovereign CDS contracts may increase and the protection of sovereign default would become more expensive. As a consequence, sovereign CDS spreads would increase. To hedge their increased sovereign default risk exposure, the default protection underwriters may short equity index, which may impose further downward pressure on equity prices.

4.2.2 Measuring the Interrelationship across Assets

Several models are employed by researchers to study the interactions across financial assets. For example, VAR and VECM models can identify short-run or/and long-run linear relation (e.g., Eun and Shim, 1989; Alter and Schüler, 2012). Copula and extreme value theory are used to quantify tail-dependency (e.g., Junker et al., 2006; Ning, 2010). Another group of models consists of unconditional and conditional correlation and Kendall's and Spearman's rank correlation coefficient.

To quantify conditional correlation, Bollerslev (1990) develops a GARCH-CCC model, which is extended to GARCH-DCC model by Tse and Tsui (2002) and Engle (2002). Based on GARCH-DCC model, more advanced methods have been proposed since then. For example, Billio and Caporin (2005) introduce a Markov switching DCC (MS-DCC) model which allows an unobservable Markov chain to determine the unconditional correlation and the DCC parameters. Capplello et al. (2006) devise an asymmetric DCC (ADCC) model which considers asymmetric impact of positive and negative shocks in both conditional variances and correlations. Also, Silvennoinen and Teräsvirta (2009) propose a double smooth transition conditional correlation (DSTCC) model which permits two observable transition variables to control conditional correlation variations. Colacito et al. (2011) suggest a class of DCC-mixed-data-sampling (MIDAS) models which allow for extracting short- and long-run component specifications from dynamic correlation. As this chapter aims to study the impact of macro news on sovereign CDS and equity index, an extension of Capplello et al.'s ADCC model is employed. One of the advantages of the ADCC model is that the effects of exogenous variables on returns, volatility, and covariance/correlation of assets could be tested directly by adding the exogenous variables to conditional mean, variance, and covariance equations.

4.2.3 News Impact of Macro Events on Financial Markets

Macro news can be classified as scheduled and unscheduled news, positive and negative news, or expected and unexpected news. Table 4.1 presents a brief summary of several studies related to news impact on financial markets. As shown, different methodologies are used, such as event study, linear regression, VAR model, univariate GARCH model, and multivariate GARCH model. Also, a wide variety of assets are studied, e.g., CDS, exchange rate, stock, and bond. Among a range of macro events, this study concentrates on sovereign credit rating and major bailout events, which are associated with sovereign default risk in particular.

Prior literature separately studies the impact of sovereign rating news on sovereign CDS and equity markets. For instance, using event study method, Ismailescu and Kazemi (2010) examine the impact of sovereign rating news on sovereign CDS spreads in 22 emerging markets and find that positive events convey more information than negative events. However, in 24 EU developed countries, Afonso et al. (2012) discover that sovereign CDS spreads have stronger responses to downgrades and negative outlooks. Regarding equity index, Brooks et al. (2004) present that only downgrades significantly affect the international equity markets. Their results are robust to different currencies used to measure returns, advanced or emerging market status, and the span of rating changes. Hooper et al. (2008) conclude that sovereign rating changes have significant impact on stock index returns and volatility, and the impact is amplified for downgrades, in emerging countries, and during crisis times.

Moreover, several papers discuss the impact of bailout events on sovereign CDS market, while limited studies examine their effects on equity market. For instance, Acharya et al. (2014) theoretically model how banking and sovereign CDS spreads interact in three sub-periods, that is, pre-bailout, bailout, and post-bailout. Their two-way feedback loop between banking system and public finance suggests that bank bailouts lead to a rise of sovereign default risk. Investors may perceive the bailouts as credit risk transfers from the private sector to the public sector; thus, they change the expectations of government creditworthiness. Due to the government bailouts in the euro area, five heavily indebted states obtain an increased access to funding to support their distressed financial systems. However, as the guarantors and contributors of the rescue packages, the other Eurozone states' residual fiscal capacity is reduced and financial stability is threatened (Horváth and Huizinga, 2015). Using event study method, Horváth and Huizinga (2015) find that around the creation day of the European Financial Stability Facility (EFSF), sovereign CDS spreads of the European countries reduce with their banking systems' exposure to GIIPS (Greece, Italy, Ireland, Portugal, and Spain) government debt, but increase with their exposure to non-GIIPS government obligations.

In addition, several studies examine the spillover effect of a country's sovereign rating events on other countries' sovereign CDS or equity markets. For example, Ferreira and Gama (2007) reveal that negative rating events present more significant spillover effect across the global stock markets and short geographic distance and emerging market status amplify the spillover effect. Arezki et al. (2011) show that after controlling the dependency among sovereign CDS, equity index, and equity sub-indices of banking and insurance sectors, sovereign rating events exert significant spillover impact across countries and assets in Europe. Blau and Roseman (2014) find that European sovereign CDS spreads substantially rise around the U.S. downgrade on 05/08/2011, suggesting that the spillover of sovereign rating news exists not only within the proximate countries but also across the entire world. Drago and Gallo (2016) uncover that only downgrades have spillover effect across the Eurozone sovereign CDS markets, while Ismailescu and Kazemi (2010) find that only positive rating changes exert spillover effect on sovereign CDS spreads of emerging countries.

As suggested by Andersen et al. (2007), the intuition of studying news impact on asset correlation is to assess whether the correlation simply shows the general interrelation among assets or it can be affected by macro event announcements. Brenner et al. (2009) summarise the reasons why asset correlation is expected to change when macro news is released, which include information spillovers across markets (e.g., Karolyi and Stulz, 1996), wealth effects of convergence traders (e.g., Kyle and Xiong, 2001), portfolio rebalancing of cross-market hedging (e.g., Fleming et al., 1998), and raised degree of disagreement among investors (e.g., Kallberg and Pasquariello, 2008). Brenner et al. (2009) state that multi-asset trading activities caused by these reasons translate into the variation of comovement across assets. Empirically, Karolyi and Stulz (1996) do not find that the U.S. macroeconomic news and other macro news releases have impact on the U.S. and Japanese stock correlation. Around the arrival of the U.S. economic news, Brenner et al. (2009) find either more negative or less positive correlation across the U.S. stock, government bond, and corporate bond markets. Chui and Yang (2012) show that the extreme correlation of stock–bond futures in the U.S., the U.K., and Germany is driven by the U.S. economic news, business cycle, and stock market uncertainties.

Based on the literature reviewed in Section 4.2.1, generally, higher (lower) sovereign default risk is related to higher (lower) sovereign CDS spread and lower (higher) equity index price. Therefore, sovereign CDS spread and equity index price are negatively correlated (Kapadia and Pu, 2012). According to Chan et al. (2009) and Ngene et al. (2014), trades between these two markets may exist for the purposes of arbitrage and hedging. When sovereign credit risk news arrives, arbitrageurs and hedgers might be more active to rebalance their positions in the two markets to earn profits and/or hedge risk (e.g., Kyle and Xiong, 2001; Fleming et al., 1998). Consequently, sovereign CDS spread and equity index price are likely to be more negatively correlated due to possibly increased cross-asset trading activities (Kapadia and Pu, 2012; Brenner et al., 2009). Accordingly, the following hypotheses are tested.

Hypothesis 1(a): Sovereign CDS and equity index markets become more correlated at the arrivals of domestic sovereign rating events.

Hypothesis 1(b): Sovereign CDS and equity index markets become more correlated at the arrivals of bailout events.

Although limited research has compared the direction and the size of the impact exerted by sovereign rating and bailout events on financial markets, bailout events are expected to have more significant and pronounced effects. One possible reason is that in contrast with rating events, major bailouts are relatively infrequent and tend to occur during the extremely stressful periods. Also, bailout events are more likely to be viewed as severe adverse shocks because taxpayers in the relevant countries have to assume all the costs (Acharya et al., 2014). However, sovereign rating events are not necessarily negative news, and essentially, they reflect mainly opinions about sovereign creditworthiness provided by a third-party. Therefore, we test the following hypothesis.

Hypothesis 2: Bailout events have stronger effects on the correlation of sovereign CDS and equity index than domestic sovereign rating events.

Based on the aforementioned literature of the spillover effect of one country's sovereign rating news on financial markets in other countries, similar economic conditions, global business, competition in international trade, common creditor, membership in a trade bloc, and geographic proximity are the possible transmission channels (Ismailescu and Kazemi, 2010). Given that the U.S., the U.K., and the Eurozone members are closely linked by global trades and/or geographic proximity, Greek sovereign rating events are likely to produce spillover effect. When Greek credit risk news arrives, arbitrageurs and hedgers might be motivated to rebalance their positions in sovereign CDS and equity markets in other economies; thus, the two markets in those countries are expected to be more correlated (e.g., Kyle and Xiong, 2001; Brenner et al., 2009).

Hypothesis 3: Sovereign CDS and equity index markets become more correlated at the arrivals of Greek sovereign rating events.

4.3 Methodology

4.3.1 Sovereign Credit Rating Events

4.3.1.1 Positive and Negative Rating Events

Sovereign credit rating information of the three major rating agencies—Moody's, S&P Global Ratings, and Fitch's ratings—is employed. Historical sovereign ratings and outlook/watchlist assessments for local currency denominated long-term government debt are utilised.[32] According to S&P Global Ratings, distinct from actual rating actions, outlooks are the assessments on the potential changes in the direction of a credit rating over next six months to two years, and watchlists deliver the rating agency's opinions

[32] As noted by Brooks et al. (2004), although there is not a 100% correspondence between local and foreign currency ratings, a change in one triggers a change in the other 75% of the time. Hence, this chapter focuses on local currency ratings for one sovereign.

about the potential direction of a short-term or long-term rating actions. Although outlooks/watchlists do not necessarily guarantee likely future rating movements, they can be considered as a signal or forecast of the subsequent rating changes (Gande and Parsley, 2005). Hence, focusing only on rating actions may omit important information and it is worth of considering both rating actions and outlooks/watchlists.

This study follows Gande and Parsley (2005) and Ferreira and Gama (2007) to construct a comprehensive credit rating (CCR) measure and use the changes of CCR to define rating events. The first step is numerically coding the explicit sovereign credit ratings (ECR) on a scale from 0 (the lowest rating, SD/D or RD/D) to 20 (the highest rating, AAA or Aaa). Next, the CCR is obtained by adding the outlook/watchlist information (on a scale from -1 for a negative outlook to 1 for a positive outlook) to the ECR. Third, any non-zero changes in the CCR is defined as rating events. Then, the rating events are further divided into 'positive rating event' (a positive change due to an upgrade, a positive outlook, or a positive credit watch) and 'negative rating event' (a negative change due to a downgrade, a negative outlook, or a negative credit watch). Table 4.2 describes the CCR definition.

However, different from Gande and Parsley (2005) and Ferreira and Gama (2007) who focus on only one rating agency, this study considers all the three major rating agencies. One reason is that three agencies may not simultaneously release the rating information for one sovereign. Also, they may have divergent views about one country's rating and outlook. For example, on 05/08/2011, S&P Global Ratings downgraded the U.S. long-term sovereign rating to AA+ from AAA, with a negative outlook. However, Moody's and Fitch only released a negative outlook on 02/06/2011 and 28/11/2011, respectively, but did not downgrade the U.S. government debt. Moreover, as discussed by Alsakka and ap Gwilym (2010), there are lead-lag relations among three agencies to provide sovereign ratings. Moody's tends to lead upgrades, while S&P Global Ratings generally leads downgrades. Therefore, only relying on the rating information offered by single rating agency may not capture all the sovereign rating changes. To construct a relatively general CCR, we repeat the above four steps for each agency and then aggregate the CCRs of three agencies.[33] For one country, if more than one rating agency releases rating news on the same day, the largest CCR change is adopted.

4.3.1.2 'Surprise Component' of Rating Actions

Suppose a country's rating at time $t-1$ is X. X is a numerical value transformed from the ECR by using the method described in Section 4.3.1.1. There are three cases: a) If at time $t-1$, outlook is 'Stable' or credit watch is 'Developing' (CW-Dev), it would be surprising if the rating at t is $X+A$ or $X-B$ (A and B are positive integer). Then, the 'surprise component' is A $(=X+A-X)$ or $-B$ $(=X-B-X)$, b) If at time $t-1$, outlook is 'Positive' or credit watch is 'Positive' (CW-Pos), it would be surprising if the rating at t is $X-B$. Then, the 'surprise component' is $-B$, and c) If at time $t-1$, outlook is 'Negative' or credit watch is 'Negative' (CW-Neg), it would be surprising if the rating at t is $X+A$. Then, the 'surprise component' is A. While Böninghausen and Zabel (2015) and Drago and Gallo (2016) use dummy variable to control anticipation effects of outlooks/watchlists, dummy variable indicates neither the sign nor the size of the predicted component of the subsequent rating actions. Table 4.3 describes the definition of 'surprise component' of one country's sovereign rating changes.

4.3.2 Bailout Events

[33] Although Afonso et al. (2012) also consider applying the three agencies' sovereign rating information, they assign an arbitrary weight to each agency's CCR and calculate an average CCR. To avoid any possible bias induced by the arbitrary weights, this study aggregates rather than averages the three CCRs.

Because of the long lists of the bailouts during the recent financial crises, this chapter considers only the major bailouts which may significantly affect sovereign default risk in the United States and the United Kingdom.[34] In the U.S., the Emergency Economic Stabilization Act of 2008 and the bailouts of Bear Stearns, Fannie Mae, Freddie Mac, and AIG are examined. In the U.K., the announcements of the second rescue package and the Special Resolution Regime are considered. In the euro area, due to the closely interconnected relationships across the members, this study focuses on the bailouts of indebted sovereigns instead of the domestic bailouts in individual countries.[35] To be specific, we examine the creations of three funding facilities, the European Financial Stability Facility (EFSF), the European Financial Stabilisation Mechanism (EFSM), and the European Stability Mechanism (ESM), and the bailouts of five distressed states (Spain, Portugal, Ireland, Cyprus, and Greece). The dates and brief descriptions of these bailout events are presented in Appendix 4A. A dummy variable, which equals one on the announcement day and zero otherwise, is constructed to define bailout event.

4.3.3 ADCC-X Model

This study modifies Vargas's (2008) ADCC-X model which is based on Capplello et al.'s (2006) ADCC model. Unlike other DCC models, the ADCC model allows for asset-specific news impact and smoothing parameters and permits asymmetric reactions in both conditional variances and correlations to negative past innovations (Capplello et al., 2006). Our ADCC-X model is slightly different from Vargas's model as it simultaneously and directly examines the impact of exogenous variables on conditional returns, volatility, and covariance of assets. The model specifications are as follows:

[34] Taken the U.S. for example, a list of bailouts is available at: http://projects.propublica.org/bailout/list.
[35] Petrovic and Tutsch (2009) offer a detailed review of the rescue measures in each European country.

$$R_{1t} = \theta_1 + \sum_{k=1}^{K} \gamma_{1k} R_{1t-k} + \sum_{k=1}^{K} \varphi_{1k} R_{2t-k} + \sum_{m=1}^{M} \delta_{1\mathrm{m}} Event_{mt} + \varepsilon_{1t} \quad (4.1)$$

$$R_{2t} = \theta_2 + \sum_{k=1}^{K} \gamma_{2k} R_{1t-k} + \sum_{k=1}^{K} \varphi_{2k} R_{2t-k} + \sum_{m=1}^{M} \delta_{2\mathrm{m}} Event_{mt} + \varepsilon_{2t} \quad (4.2)$$

$$log\, h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\, log\, h_{1t-1} + d_1 \frac{\varepsilon_{1t-1}}{\sqrt{h_{1t-1}}} + \sum_{m=1}^{M} \lambda_{1\mathrm{m}} Event_{mt} \quad (4.3)$$

$$log\, h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\, log\, h_{2t-1} + d_2 \frac{\varepsilon_{2t-1}}{\sqrt{h_{2t-1}}} + \sum_{m=1}^{M} \lambda_{2\mathrm{m}} Event_{mt} \quad (4.4)$$

EGARCH with asymmetry model is the major univariate model applied in this study because it guarantees the positivity of the conditional variance and does not require any restrictions on parameters.[36] R_{1t} and R_{2t} are the first log-difference of sovereign CDS spread and equity index price, respectively. To capture autocorrelation in return series and possible lead-lag relation between asset returns, lags of R_{1t} and R_{2t} are included. Lag K is selected based on Schwarz Information Criterion (SBC). h_{1t} and h_{2t} are the conditional variance of the returns of sovereign CDS and equity index, respectively. $Event_{mt}$ denotes the mth macro event and M is the total number of event categories. Let the covariance matrix of two asset returns be H_t and H_t is decomposed as:

$$H_t = D_t P_t D_t \quad (4.5)$$

D_t is the 2×2 diagonal matrix of time-varying standard deviations with $\sqrt{h_{it}}$ on the ith diagonal, and P_t is the time-varying correlation matrix. Standardise the residuals, ε_{it}, and use them to estimate covariance parameters. The following covariance dynamic allows for asset-specific news and smoothing parameters, asymmetries, and effects of exogenous variables:

[36] As pointed out by Capplello et al. (2006), if the univariate models are not well specified, the correlation estimation would be inconsistent. Therefore, if for one country's sovereign CDS and/or equity index, the EGARCH with asymmetry model has convergence issues, GARCH, EGARCH without asymmetry, GJR, EGARCH with/without asymmetry with student's t innovation, and GJR with student's t innovation would be tried to achieve convergent results.

$$Q_t = (\bar{P} - \alpha^2\bar{P} - \beta^2\bar{P} - g^2\bar{N} - \sum_{m=1}^{M} Kv_m\overline{Event_m}) + \alpha^2\varepsilon_{t-1}\varepsilon'_{t-1} + g^2 n_{t-1}n'_{t-1} + \beta^2 Q_{t-1} + \sum_{m=1}^{M} Kv_m Event_{mt} \quad (4.6)$$

where $\alpha, \beta, g,$ and v_m are scalars, and $K = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$.[37] $\bar{P} = E[\varepsilon_t\varepsilon'_t] = T^{-1}\sum_{t=1}^{T}\varepsilon_t\varepsilon'_t$, $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$, $\bar{N} = E[n_t n'_t] = T^{-1}\sum_{t=1}^{T} n_t n'_t$, and $\overline{Event_m} = E[Event_{mt}] = T^{-1}\sum_{t=1}^{T} Event_{mt}$. v_m measures the magnitude and significance level of the impact of the mth macro event on the covariance of two assets.

4.4 Data

4.4.1 Sovereign CDS and Equity Index

Sovereign CDS and equity index data are obtained from DataStream. Due to sovereign CDS data availability, the sample period is from 01/01/2008 to 29/02/2016. Also, the restructuring type of sovereign CDS contract is Complete Restructuring (CR), as it is the only restructuring clause applied by the sovereign CDS series, and 5-year contracts are selected. Given the sample period, Estonia, Latvia, and Lithuania, who joined in the Eurozone after 2008, are excluded. Also, Luxembourg, Malta, and Greece are removed due to unavailable or insufficient sovereign CDS data. The final sample consists of 14 developed countries. The equity indices used in this study are described in Appendix 4B. Summary statistics of CDS spreads and equity index prices are presented in Table 4.4. Germany has the lowest and the least volatile sovereign CDS spreads, followed by the U.S., Finland, and Netherlands. Cyprus has the highest and the most volatile country

[37] Vargas (2008) suggests using $K = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ or $K = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Using matrix of ones or identity matrix, one can examine the impact of exogenous variables on conditional variance-covariance or variance of assets. However, by employing $K = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, we directly investigate the impact of exogenous variables on conditional covariance/correlation of assets.

default risk, followed by Portugal and Ireland. Regarding equity index price, Italy and Slovenia have the most and the least volatile index prices, respectively.

4.4.2 Sovereign Credit Rating Events

Table 4.5 reports the number of sovereign credit rating events in each country. As shown in Table 4.5, the total number of negative and positive rating events (including the number of Greek rating events) is 195 and 89, respectively. As the sample period covers the global financial crisis and the European sovereign debt crisis, the number of negative rating events is more than two times that of positive rating events. In contrast with the other countries, GIIPS countries and Cyprus have more negative rating events.

Table 4.6 reports the number of rating surprises in each country. Eight of the fourteen countries have sovereign rating surprises. Among them, Cyprus, Ireland, Italy, Portugal, and Spain suffered from financial difficulties in the European sovereign debt crisis. The total number of rating surprises is 22, including 8 negative surprises and 14 positive surprises. Unlike the sovereign rating events reported in Table 4.5, the number of positive surprises is almost two times that of negative surprises, and the total number of rating surprises is far less than that of rating events.

4.5 Empirical Results

4.5.1 Impact of Domestic Sovereign Rating Events

Table 4.7 presents the test results of domestic sovereign credit rating events.[38] The table shows that domestic sovereign rating events (δ_1) exert impact on sovereign CDS returns in Portugal, Ireland, Cyprus, and Slovenia. In these four Eurozone countries, sovereign

[38] To keep brevity, this table only reports the key coefficients which are of the interest of this chapter. All the tables, from Table 4.7 to Table 4.18, are presented in the same manner. The full estimation results can be found in Appendix 4C.

CDS returns significantly decline when domestic sovereign rating changes, indicating lower sovereign default probabilities. Rating events (δ_2) only have impact on equity returns in Germany and the United Kingdom. They increase Germany's DAX 30 Index returns, but reduce the U.K.'s FTSE 100 Index returns. Also, rating events (λ_1) increase sovereign CDS volatility in Ireland, Austria, Finland, and the U.K., but decrease that in Portugal and Cyprus. Except for the U.S., no significant effect of rating events (λ_2) on equity volatility is discovered in the rest of 13 European members. In addition, rating events (v) increase the negative correlation between sovereign CDS and equity index in Portugal, Italy, Netherlands, Austria, and the U.S., while they reduce the negative correlation in Finland. An increased negative correlation may suggest a lower degree of correlation between the two assets when domestic sovereign rating events occur.

In roughly one third of the 13 European economies, especially the indebted states in the European sovereign debt crisis, domestic sovereign rating events considerably affect returns and volatility of sovereign CDS. However, for equity index, the rating news seems to be irrelevant. These results are generally inconsistent with prior findings that sovereign rating news can arouse considerable variations of asset prices, e.g., Hooper et al. (2008). This may be ascribed to several reasons. First, the domestic rating events examined in this section consist of positive and negative rating events. As suggested by previous research, e.g., Afonso et al. (2012) and Ismailescu and Kazemi (2010), these two types of rating news present opposite influences on financial markets. Hence, their combined effects may explain the complex patterns of the impact of rating events. This confirms the necessity to analyse them separately. Second, the relevant literature to date employs event study method, focuses only on asset returns, or defines rating events based on single rating agency's information. However, we use a multivariate GARCH model that allows for simultaneously testing news impact on returns, volatility, and correlation of assets, and we aggregate three major agencies' rating news. Moreover, except for Drago and Gallo (2016), the sample periods of previous studies do not cover the turmoil period after 2008, e.g., Ismailescu and Kazemi (2010). On the contrary, this chapter focuses on the relatively turbulent period of 2008–2016. For asset correlation, Hypothesis 1(a) is not well supported because limited evidence is found to support the expectation that two assets become more correlated at the arrivals of domestic sovereign rating events. However, two assets become less negatively correlated. One possible reason is that there are limited cross-asset trading activities at the arrival of sovereign rating news. This may be due to any impediments to arbitrage, e.g., funding constraints and market liquidity (Kapadia and Pu, 2012). Another reason is that there are cross-asset trading activities, but the trades result in a less negative correlation between the two assets (Brenner et al., 2009).

4.5.2 Impact of Domestic Positive and Negative Sovereign Rating Events

In order to examine whether the impact of sovereign rating events on the two assets is depend on the nature of the news, we test the impact of domestic good and bad rating events. As can be seen from Table 4.8[39], both symmetric and asymmetric effects on two assets are found. In Portugal, Netherlands, Finland, and the U.S., sovereign CDS returns respond symmetrically to two types of rating events (δ_{11} is for positive news and δ_{12} is for negative news). Except the U.S., two rating events increase sovereign CDS returns. For equity index, two rating events (δ_{21} is for positive news and δ_{22} is for negative news) reduce equity returns in Spain and Germany. The asymmetric impact of two rating events on sovereign CDS returns is found in Ireland, Cyprus, and Belgium, and their asymmetric impact on equity returns is discovered in Cyprus and the United

[39] As no convergent univariate GARCH model estimation results of Austria and Slovenia can be obtained, these two countries are dropped.

Kingdom. Good (bad) rating events reduce (increase) sovereign CDS returns in Ireland and Cyprus, while the opposite case is found in Belgium. In Cyprus, good (bad) rating events are accompanied by higher (lower) equity returns, while in the U.K., the situation is reversed. The asymmetric effects marginally support the commonly held perception that negative (positive) rating events suggest an increase (decrease) in sovereign default probability or country risk, so that sovereign CDS spreads widen (narrow) and equity prices fall (increase) (e.g., Afonso et al., 2012; Hooper et al., 2008). Compared with bad rating news, good rating news generally exerts more pronounced—in absolute values—impact on asset returns.

Second, the effects of two rating events (λ_{11} is for positive news and λ_{12} is for negative news) on sovereign CDS volatility are discovered in eight economies. In five of these eight states, two rating events have calming impact on spread volatility. However, good (bad) rating events increase (reduce) spread volatility in Ireland and the U.K., while the opposite case is found in Portugal. Regarding equity volatility, two rating news (λ_{21} is for positive news and λ_{22} is for negative news) resolves (creates) uncertainties in Ireland (Belgium). However, in Spain, Netherlands, and the U.S., equity volatility falls (increases) in response to positive (negative) rating events. For volatility of two assets, the absolute magnitudes of the effects of good rating events are greater than that of bad rating events. Kim et al. (2015) also document that good macro news has stronger impact than bad macro news on sovereign CDS volatility. They interpret that sovereign CDS investors may concern more about good news than bad news, especially during the stressful episodes. Since the sample period of this study is from 2008 to 2016, which covers the subprime crisis, the European sovereign debt crisis, and the turbulent post-crisis period, our findings may be supported by Kim et al.'s (2015) argument.

Finally, for the correlation between sovereign CDS and equity index, symmetric effects of two rating events (v_1 is for positive news and v_2 is for negative news) exist in Spain, Italy, and Cyprus. When good or bad rating events occur, the negative correlation of the two assets drops in Spain and Italy, but it increases in Cyprus. Good (bad) rating events are related to a rise (decline) of asset negative correlation in Portugal, the U.S., and Netherlands, while an opposite situation is found in Ireland and Finland. Although good rating news has more pronounced effects—in absolute values—on the correlation between two assets, bad news shows more significant impact. These findings imply that the impact of domestic sovereign rating events on asset correlation might vary with the nature of the events, while the news impact may not be necessarily asymmetric. Using a DCC-IMA model, Brenner et al. (2009) reveal that increased portfolio rebalancing activities within or across asset classes are more likely to occur in correspondence with the unexpected negative macroeconomic news releases.

4.5.3 Impact of Domestic Sovereign Rating Surprises

Table 4.9 reports the results of domestic sovereign rating surprises.[40] Rating surprises (δ_1) reduce sovereign CDS returns in Cyprus and Ireland. It suggests that the arrivals of rating surprises may signal a decline of sovereign default risk. However, in all the six countries, we find no significant impact of rating surprises (δ_2) on equity returns. Rating surprises (λ_1) decrease sovereign CDS volatility in Cyprus but increase spread volatility in Ireland. Similar to equity returns, no significant effects of rating surprises (λ_2) on equity volatility are found. Finally, in Austria, Cyprus, and Italy, the negative correlation of two assets goes up when rating surprises (v) occur, suggesting a rise of the negative correlation. These results are generally consistent with the findings in

[40] Since no convergent univariate GARCH results of Portugal and Slovenia can be obtained, they are excluded.

Section 4.5.1. Although domestic sovereign rating surprises can affect returns and volatility of sovereign CDS, they have limited impact on equity index. Rating surprises are associated with a lower degree of correlation between the two assets.[41]

Taken the findings in Section 4.5.1–4.5.3 collectively, domestic sovereign rating events and rating surprises generally deliver tradable information to two asset markets in less than half of the sample countries. It may imply that at least for equity markets in these countries, domestic sovereign rating news may not be as informative as emphasised by prior studies, such as Brooks et al. (2004). Apart from the possible reasons mentioned in Section 4.5.1, the ineffectiveness of sovereign rating information may also explain the contradictory conclusions. As stated by Masciandaro (2013), there are three reasons why rating news may be ineffective, especially for sovereign obligors. First, sovereign credit ratings may not benefit from information advantages because rating agencies are less likely to have the access to privileged information about sovereigns. Second, the adequacy of human capital and the quality of methodology used by rating agencies are questioned since their welfares may not be attractive to the best human capital. Finally, biased behaviour may hinder the rating agencies from delivering objective, timely, and accurate rating information.

4.5.4 Impact of Bailout Events

Table 4.10 shows the results of bailout events. Bailout announcements (δ_1) increase sovereign CDS returns in Spain, Italy, and Cyprus, while they reduce sovereign CDS returns in Portugal. All these four states suffered from severe financial difficulties during the European sovereign debt crisis, and except for Italy, the other three states

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[41] Although rating surprises are also divided into positive and negative surprises (Table 4.6), only four states, Cyprus, Ireland, Spain, and Slovenia, have two types of rating surprises. Moreover, convergent estimation results can be obtained in only Spain and Ireland. Thus, the estimation results about the impact of positive and negative rating surprises are not reported.

are the beneficiaries of the rescue plans of the Eurozone. It seems that the government bailouts in the euro area have more material influences on sovereign CDS returns of the indebted states rather than on that of the guarantors of bailouts. In Portugal, Italy, Germany, France, and Finland, equity market performs worse on the day when bailout news (δ_2) is released. These affected countries include both receivers and providers of bailout funding. The increased sovereign CDS returns and the declined equity returns suggest that bailout events are likely to be perceived to weaken a country's sovereign creditworthiness and economic condition (Acharya et al., 2014; Horváth and Huizinga, 2015). Bailout news releases (λ_1) increase sovereign CDS volatility in nine states and they (λ_2) increase equity volatility in seven countries, confirming that investors are inclined to interpret bailout actions as extremely adverse shocks. Thus, this macro event induces more uncertainties and destabilises financial markets. Finally, except for Italy, Cyprus, Austria, and Netherlands, sovereign CDS and equity index become more negatively correlated on the bailout announcement days (v), which supports Hypothesis 1(b). The strengthened negative comovement may stem from more cross-asset arbitrage and/or hedging activities between sovereign CDS and equity markets on the release days of bailouts, which supports Chan et al. (2009) and Ngene et al. (2014).

4.5.5 Impact of Bailouts and Domestic Sovereign Rating Events

Table 4.11 reports the results of bailouts and domestic rating events. Domestic rating events (δ_{11}) reduce sovereign CDS returns in Portugal, Ireland, and Cyprus, while they increase spread returns in Belgium. They (δ_{21}) increase equity returns in Germany. For volatility, rating events (λ_{11}) are associated with higher spread volatility in Ireland, Austria, Slovenia, Finland, and the U.K., and they are related to lower spread volatility in Portugal and Cyprus. Moreover, they (λ_{21}) have negative effects on equity volatility in the United States. In Spain, Italy, Netherlands, Austria, and Finland, rating events (v_1) increase the negative asset correlation. Bailout events (δ_{12}) reduce sovereign CDS returns in Portugal, Belgium, and the U.K., but increase that in Spain. They (δ_{22}) lower equity returns in Spain, Italy, Ireland, Germany, France, and Finland. In the majority of the 14 countries, bailout events (λ_{12} is for sovereign CDS and λ_{22} is for equity) increase asset volatility, and they (v_2) are accompanied by a lower negative correlation of two assets. Finally, compared with domestic sovereign rating events, bailout news seems to exert stronger and more significant impact on asset volatility and correlation, which is in line with Hypothesis 2. This may suggest that relatively more cross-asset arbitrage and/or hedging activities between sovereign CDS and equity markets may exist on the release days of bailout events than on that of domestic sovereign rating events.

4.5.6 News Spillover Effect of Greek Sovereign Rating Events

This study also shows that Greek sovereign rating events present spillover effect on the sample countries' sovereign CDS and equity markets. The results are reported in Table 4.12.[42] First, in Portugal, Ireland, Cyprus, Slovenia, the U.S., and the U.K., Greek rating events (δ_{12}) reduce sovereign CDS returns, indicating a decrease of sovereign default risk. In six Eurozone countries and the U.S., equity returns increase when Greek rating (δ_{22}) changes, suggesting declined country risk. Moreover, sovereign CDS volatility reduces in response to Greek rating news (λ_{12}) in eight Eurozone states. The news (λ_{22}) lowers equity volatility in Ireland, but increases that in Slovenia. In Portugal, Germany, France, Belgium, the U.S., and the U.K., the negative correlation of two assets increases when Greek rating events (v_2) occur.

[42] Since no convergent univariate GARCH estimations of Finland can be gained, this state is excluded.

These findings suggest that Greek rating news may signal the resolution of uncertainty about sovereign default risk. Thus, in the sample states, sovereign CDS spreads narrow and spread volatility declines. The negative correlation generally increases when Greek rating news arrivals, which conflicts with Hypothesis 3. It implies that although Greek rating events have spillover effect, they may not cause more cross-asset arbitrage and/or hedging activities between sovereign CDS and equity markets. In contrast to domestic rating events, equity investors seem to concern more about Greek rating news. Due to the important role played by Greece in the European sovereign debt crisis, Greek credit condition may become an important factor considered by international equity investors to make investment decisions. It seems to support Gande and Parsley's (2005) argument of 'common information spillovers'. Overall, our results suggest that Greek rating news generally delivers information to sovereign CDS and equity markets in the sample countries, which supports the literature of spillover effect of sovereign rating events, e.g., Ismailescu and Kazemi (2010), Afonso et al. (2012), and Blau and Roseman (2014).

4.5.7 Additional Analysis and Robustness Test

There is another approach to test the impact of macro events on conditional correlation between two assets. An ADCC model is estimated first and then the correlation is extracted. After obtaining the correlation, this chapter follows Chiang et al. (2015) to apply a Fisher transformation on the correlation to resolve the issue that the correlation is bounded to an interval [-1, 1] and conducts regression analysis. The equation (4.6) is changed to be:

$$Q_t = (\bar{P} - \alpha^2\bar{P} - \beta^2\bar{P} - g^2\bar{N}) + \alpha^2\varepsilon_{t-1}\varepsilon'_{t-1} + g^2 n_{t-1}n'_{t-1} + \beta^2 Q_{t-1} \tag{4.7}$$

The dynamic correlation of two assets and the linear regression are as follows:

$$\rho_{12t} = \frac{q_{12t}}{\sqrt{q_{11t}q_{22t}}} \tag{4.8}$$

$$\widetilde{\rho_{12t}} = 0.5\, ln \left[\frac{1+\rho_{12t}}{1-\rho_{12t}}\right] \quad (4.9)$$

$$\widetilde{\rho_{12t}} = \xi_0 + \sum_{m=1}^{M} \phi_m Event_{mt} + u_t \quad (4.10)$$

In Equation (4.10), robust errors are used to adjust for heteroskedasticity. As a two-step estimation process is used, the results of univariate GARCH models of sovereign CDS and equity index are the same as that reported in the corresponding tables (Table 4.7–4.12). Thus, Table 4.13–4.18 only report the estimation results of Equation (4.10).

First, as shown in Table 4.13, in Spain, Italy, France, Netherlands, Belgium, and the U.K., rating events rise the negative correlation of two assets. Second, Table 4.14 shows that in Spain, Italy, Germany, Belgium, and Finland, two assets are more negatively correlated when good or bad rating news is released. Good (bad) news increase (reduce) two assets' negative correlation in Netherlands, the U.S., and the U.K. Third, in Table 4.15, rating surprises have positive impact on the negative correlation in France, Ireland, and Italy, suggesting a lower degree of correlation, while they have negative impact on the negative correlation in Austria, implying a higher degree of correlation. Table 4.16 reports that bailout events reduce the negative correlation between the two assets in Portugal, Cyprus, Germany, France, and Belgium. However, bailout events increase the negative correlation in Austria and the U.K. In Table 4.17, contrary to domestic rating events, bailout events generally have stronger effects. Finally, Table 4.18 shows that, in Spain, Italy, and Netherlands, the two assets become more correlated when Greek rating news is released. Although the two methods provide slightly different results about the news impact on correlation in individual country, the general conclusions drawn from the entire sample seem to be consistent.

In addition, the robustness of the findings to different CCR coding methods is justified. Böninghausen and Zabel (2015) state that researchers have disagreements about how ECR is adjusted for outlook/watchlist news to obtain CCR. Gande and Parsley (2005) and Ferreira and Gama (2007) adjust the ECR by a notch (half a notch) of actual rating change according to outlook (watchlist) releases. Ismailescu and Kazemi (2010) and Drago and Gallo (2016) equate the impact of outlook (watchlist) to half (a quarter) of a notch. Also, Sy (2004) and Alsakka and ap Gwilym (2012) consider the impact of outlook (watchlist) as one third (two thirds) of a notch. This chapter employs Sy's (2004) coding approach which assumes the smallest (largest) informational content of outlooks (watchlists) among the three coding strategies. The tables in Appendix 4D describe Sy's (2004) CCR definition and the number of rating events in each country. The estimation results related to sovereign credit rating events are reported in Table 4.19–4.22. The tables show that the heterogeneity in ECR adjustment approaches does not materially change the main conclusions.

4.6 Conclusions

This chapter applies ADCC-X model to investigate the impact of sovereign credit rating events and major bailout news on returns, volatility, and correlation of sovereign CDS and equity index in the U.S., the U.K., and the Eurozone states during the turbulent period of 2008–2016. The findings show that sovereign CDS market is more sensitive to domestic sovereign credit rating events or surprises than equity market. The arrivals of rating events or surprises are generally accompanied by an increase of the negative correlation, suggesting a lower degree of correlation between the two assets. Moreover, both symmetric and asymmetric impact of positive and negative rating events on the returns and volatility of two assets is found. Regarding asset correlation, symmetric impact of two rating events is found in three countries, while their asymmetric impact is detected in five countries. To be specific, they reduce the negative correlation of two assets in Spain and Italy, while the opposite case is in Cyprus. In Portugal, Netherlands, and the U.S., the negative correlation increases (decreases) when positive (negative) sovereign rating events occur , while an opposite situation exists in Ireland and Finland. Generally, positive sovereign rating news has stronger impact on the returns, volatility, and correlation of the two assets.

Major bailout events increase sovereign CDS returns and decrease equity returns, and they exaggerate both assets' volatility. Two assets become more negatively correlated when bailout news is released. Compared with domestic sovereign rating news, bailout news exerts stronger and more significant impact. These findings may support the view that in contrast with sovereign rating events, bailout news is more likely to be perceived as extremely adverse shocks. Finally, Greek rating events produce spillover effect on the two assets in several sample countries and they generally have a positive impact on the negative correlation of two assets. Compared with domestic sovereign rating news, equity investors seem to pay more attention to Greek sovereign rating changes.

Table 4.1: Summary of Previous Literature about Macro News Impact

	Studies	Methodology	Major Findings
Positive news vs. Negative news	Kim, Salem, and Wu (2015)	Univarite EGARCH model	They focus on scheduled macroeconomic news releases and study the impact of domestic and spillover macroeconomic news from the U.S., the Eurozone, and China on sovereign CDS spreads and spread volatility. They find that good news reduces sovereign CDS spreads, while bad news increases spreads. Good news presents stronger effects, especially during the crisis times. CDS spread volatility increases when both domestic good and bad news is released, but good news has more pronounced effects. Macroeconomic news from the major countries has spillover impact on the sovereign CDS market in other countries.
	Galil and Soffer (2011)	An event study analysis	They focus only on corporate rating changes and explore the CDS market's response to rating announcements after controlling for the presence of public and private information. They confirm the previous results that CDS spreads react substantially after rating changes and rating reviews announcements. Also, negative news has stronger impact than positive news.
Scheduled news vs. Unscheduled news	Chen and Gau (2010)	Linear regression	They use Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) component share to measure price discovery contribution. Also, they use linear regression to study which market, spot or futures for EUR-USD and JPY-USD, can adjust more rapidly in response of scheduled macroeconomic announcements. Their results show that around scheduled macroeconomic releases, futures rates move more rapidly than spot rates.
	Jiang, Konstantinidi, and Skiadopoulos (2012)	VAR model	They examine the effect of the U.S. and the European scheduled (unscheduled) news announcements on volatility spillover across the U.S. and the European stock markets. Their unscheduled news consists of financial news that may dramatically shock financial markets, political news, and news about physical disasters and threats for the human life. They document that scheduled (unscheduled) news releases reduce (amplify) information uncertainty, inducing a decrease (increase) in implied volatility. Volatility spillovers cannot be entirely explained by news releases.

Table 4.1: Summary of Previous Literature about Macro News Impact (Continued)

	Studies	Methodology	Major Findings
Macroeconomic news surprise	Mun (2012)	VAR-GARCH-in-mean model	This study analyses the joint response of stock and foreign exchange market returns in the U.S. and Japan to macroeconomic surprises. The findings show that the U.S. stock market asymmetrically reacts to domestic macroeconomic surprises but is not affected by Japanese macroeconomic surprises. Also, the surprise in the foreign exchange market affect both U.S. and Japanese stock markets.
	Brenner, Pasquariello, and Subrahmanyam (2009)	DCC-Integrated Moving Average (IMA) Model	They examine the short-term response of U.S. stock, Treasury, and corporate bond markets to the first release of U.S. macroeconomic surprises. They analyse the impact of news on the level, the volatility, and comovement of those assets. Their results show a substantial difference between stock and bond markets in their reactions to the releases of macroeconomic shocks. Also, the conditional mean, volatility, and comovement among stock, Treasury, and corporate bond present different responses to the information content of macroeconomic surprises.
	Andersen, Bollerslev, Diebold, and Vega (2007)	VAR-GARCH model	They study the real-time impact of the U.S. macroeconomic news surprises on the U.S., German, and British stock, bond, and foreign exchange markets. They find that announcement surprises generate conditional mean jumps. They also document highly significant contemporaneous cross-market and cross-country interactions, even after controlling macroeconomic announcement effects.

Notes: This table briefly summarises the previous literature about news impact on financial markets.

Table 4.2: Define Comprehensive Credit Rating

Explicit Credit Rating (ECR)				Credit Outlook/Watchlist	
S&P	Moody's	Fitch	Numerical code	Information	Add to ECR
AAA	Aaa	AAA	20	Positive	1
AA+	Aa1	AA+	19	CW-Pos	0.5
AA	Aa2	AA	18	Stable/CW-Dev	0
AA-	Aa3	AA-	17	CW-Neg	-0.5
A+	A1	A+	16	Negative	-1
A	A2	A	15		
A-	A3	A-	14		
BBB+	Baa1	BBB+	13		
BBB	Baa2	BBB	12		
BBB-	Baa3	BBB-	11		
BB+	Ba1	BB+	10		
BB	Ba2	BB	9		
BB-	Ba3	BB-	8		
B+	B1	B+	7		
B	B2	B	6		
B-	B3	B-	5		
CCC+	Caa1	CCC+	4		
CCC	Caa2	CCC	3		
CCC-	Caa3	CCC-	2		
CC/C	Ca/C	CC/C	1		
SD/D		RD/D	0		

Notes: This table shows that the comprehensive credit rating is defined by adding credit outlook/watchlist information to the explicit credit rating. CW-Pos denotes Credit Watch-Positive, CW-Dev denotes Credit Watch-Developing, and CW-Neg denotes Credit Watch-Negative.

Table 4.3: Define 'Surprise Component' of Sovereign Rating Actions

Suppose for one country, rating is X at time $t-1$. $A\ and\ B$ are positive integer.			
Outlook at time $t-1$	Rating action at time t (No Surprise)	Rating action at time t (With Surprise)	The Size and the Sign of Surprise Component
Stable/CW-Dev	X	$X+A$ or $X-B$	A or $-B$
Positive or CW-Pos	$X+A$ or X	$X-B$	$-B$
Negative or CW-Neg	$X-B$ or X	$X+A$	A

Notes: This table presents the method to define and calculate sovereign rating surprises. CW-Pos denotes Credit Watch-Positive, CW-Dev denotes Credit Watch-Developing, and CW-Neg denotes Credit Watch-Negative.

Table 4.4: Summary Statistics of CDS Spreads and Equity Index Prices

	Mean	Std.	Min.	Max.
Panel A: Sovereign CDS Spread				
Austria	47.36	34.67	12.18	159.23
Belgium	72.58	61.88	14.50	341.98
Cyprus	475.56	423.01	14.00	1,674.22
Finland	33.01	18.47	9.25	94.00
France	47.75	33.45	6.00	171.56
Germany	24.21	16.97	5.20	92.50
Ireland	241.58	229.58	29.28	1,191.16
Italy	155.39	104.29	21.13	498.66
Portugal	330.15	322.81	23.50	1,521.45
Spain	149.54	103.22	19.75	492.07
Slovenia	151.70	105.43	8.00	448.67
Netherlands	46.55	30.20	6.25	133.84
U.S.	32.07	15.71	6.00	95.00
U.K.	49.41	28.37	11.66	165.00
Panel B: Equity Index Price				
Austria	919.69	87.72	681.26	1,142.47
Belgium	2,755.68	563.43	1,527.27	4,127.47
Cyprus	816.39	961.56	63.85	4,880.97
Finland	6,867.94	1,210.13	4,110.31	10,178.31
France	3,942.99	603.98	2,519.29	5,614.08
Germany	7,501.73	1,958.93	3,666.41	12,374.73
Ireland	3,833.91	1,280.93	1,916.38	6,886.56
Italy	20,393.93	4,592.56	12,362.51	38,553.67
Portugal	6,657.05	1,411.79	4,408.73	11,368.40
Spain	9,884.99	1,601.04	5,956.30	15,182.30
Slovenia	358.71	66.25	199.25	509.24
Netherlands	869.18	366.32	418.23	2,520.56
U.S.	1,457.95	383.07	676.53	2,130.82
U.K.	5,853.14	783.72	3,512.09	7,103.98

Notes: This table presents the summary statistics of sovereign CDS spreads and equity index prices of each country. CDS spreads are expressed in basis points.

Table 4.5: Number of Sovereign Rating Events in Each Country

Country	No. of Rating Events	No. of Negative Rating Events	No. of Positive Rating Events
Austria	6	5	1
Belgium	13	9	4
Cyprus	43	28	15
Finland	6	5	1
France	7	7	0
Germany	4	2	1
Greece	56	42	14
Ireland	33	20	13
Italy	15	11	4
Portugal	33	21	12
Spain	31	21	10
Slovenia	23	16	7
Netherlands	7	4	3
U.S.	5	2	3
U.K.	3	2	1
Total	284	195	89

Notes: This table reports the total number of sovereign credit rating events and the numbers of positive and negative rating events in each country.

Table 4.6: Number of Sovereign Rating Surprises in Each Country

Country	No. of Surprises	No. of Negative Surprises	No. of Positive Surprises
Austria	1	1	0
Cyprus	6	1	5
France	1	1	0
Ireland	4	1	3
Italy	1	1	0
Portugal	1	0	1
Spain	5	1	4
Slovenia	3	2	1
Total	22	8	14

Notes: This table reports the total number of sovereign credit rating surprises and the number of positive and negative rating surprises in each country.

Table 4.7: Estimation Results of Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
δ_1 (Rating Events)	-0.940*	-0.043	-0.296	-1.164***	-0.194***
	(0.070)	(0.931)	(0.647)	(0.000)	(0.000)
λ_1 (Rating Events)	-0.262***	-0.096	0.039	0.188***	-0.352***
	(0.000)	(0.127)	(0.729)	(0.003)	(0.000)
δ_2 (Rating Events)	0.029	0.090	0.329	0.116	0.024
	(0.806)	(0.595)	(0.271)	(0.323)	(0.702)
λ_2 (Rating Events)	-0.021	-0.039	-0.098	0.045	0.018
	(0.761)	(0.453)	(0.146)	(0.470)	(0.745)
v (Rating Events)	0.069**	0.012	0.023***	-0.046	-0.018
	(0.032)	(0.286)	(0.005)	(0.114)	(0.785)
	Germany	France	Netherlands	Belgium	Austria
δ_1 (Rating Events)	2.726	0.010	-0.204	0.400	-1.216
	(0.503)	(0.996)	(0.864)	(0.634)	(0.318)
λ_1 (Rating Events)	-0.090	0.089	0.271	-0.180	0.528***
	(0.929)	(0.686)	(0.482)	(0.400)	(0.000)
δ_2 (Rating Events)	1.757*	0.166	0.110	0.105	-0.368
	(0.054)	(0.723)	(0.731)	(0.606)	(0.300)
λ_2 (Rating Events)	-0.149	-0.087	-0.318	0.034	-0.243
	(0.724)	(0.504)	(0.140)	(0.753)	(0.268)
v (Rating Events)	0.203	-0.035	0.740***	0.017	0.441***
	(0.240)	(0.541)	(0.000)	(0.739)	(0.000)
	Slovenia	Finland	U.S.	U.K.	
δ_1 (Rating Events)	-0.047*	0.278	-1.542	-0.086	
	(0.085)	(0.555)	(0.351)	(0.845)	
λ_1 (Rating Events)	0.080	0.889**	0.001	3.836***	
	(0.158)	(0.022)	(0.999)	(0.003)	
δ_2 (Rating Events)	-0.072	0.159	0.416	-0.639*	
	(0.518)	(0.668)	(0.110)	(0.056)	
λ_2 (Rating Events)	0.110	0.147	-0.747***	-0.059	
	(0.482)	(0.455)	(0.001)	(0.887)	
v (Rating Events)	-0.009	-0.685***	0.418***	-0.044	
	(0.863)	(0.000)	(0.000)	(0.345)	

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is rating events. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.8: Estimation Results of Domestic Positive and Negative Sovereign Rating Events

	Portugal	Spain	Italy	Ireland (GARCH)	Cyprus	Germany
δ_{11} (Positive	0.027**	-0.228	-2.296	-1.835***	-0.016***	1.439
Rating Events)	(0.021)	(0.810)	(0.120)	(0.001)	(0.000)	(0.734)
δ_{12} (Negative	-1.376***	0.017	-0.069	-1.131**	-0.748***	2.952
Rating Events)	(0.000)	(0.976)	(0.888)	(0.011)	(0.003)	(0.466)
λ_{11} (Positive	-0.333	-0.031	-0.486	1.323**	-0.857***	-3.384
Rating Events)	(0.222)	(0.870)	(0.248)	(0.040)	(0.000)	(0.205)
λ_{12} (Negative	-0.260***	-0.106	0.074	0.202	0.137***	0.369
Rating Events)	(0.002)	(0.167)	(0.484)	(0.843)	(0.000)	(0.701)
δ_{21} (Positive	-0.231	-0.194	0.352	-0.067	0.028***	-0.875
Rating Events)	(0.586)	(0.471)	(0.644)	(0.784)	(0.000)	(0.737)
δ_{22} (Negative	0.066	0.267***	0.328	0.139	0.012	2.426**
Rating Events)	(0.612)	(0.000)	(0.317)	(0.122)	(0.897)	(0.047)
λ_{21} (Positive	0.135	-0.285*	0.002	-0.125	0.034	0.382
Rating Events)	(0.544)	(0.051)	(0.995)	(0.299)	(0.698)	(0.706)
λ_{22} (Negative	-0.041	-0.019	-0.088	0.142***	0.013	-0.264
Rating Events)	(0.567)	(0.693)	(0.203)	(0.000)	(0.834)	(0.546)
v_1 (Positive	0.035	-0.017	-0.032	-0.001	0.097**	-0.198
Rating Events)	(0.808)	(0.348)	(0.537)	(0.987)	(0.018)	(0.691)
v_2 (Negative	0.069**	0.015**	0.021***	-0.083*	-0.040	0.319
Rating Events)	(0.017)	(0.049)	(0.008)	(0.053)	(0.105)	(0.130)
	France(GJR)	Netherland	Belgium	Finland	U.S.	U.K.
δ_{11} (Positive		1.912***	0.648	1.510***	-2.373**	5.211
Rating Events)		(0.002)	(0.310)	(0.001)	(0.030)	(0.794)
δ_{12} (Negative	0.262	-2.192***	0.462***	-0.024	2.110	-0.106
Rating Events)	(0.882)	(0.008)	(0.000)	(0.953)	(0.176)	(0.756)
λ_{11} (Positive		-0.779**	-1.454***	-2.666***	-0.827*	2.923*
Rating Events)		(0.042)	(0.000)	(0.001)	(0.085)	(0.083)
λ_{12} (Negative	5.072	1.340***	0.218	1.572***	0.672**	4.382***
Rating Events)	(0.329)	(0.000)	(0.282)	(0.000)	(0.043)	(0.001)
δ_{21} (Positive		-0.426	-0.096	-0.281	0.371	-0.911***
Rating Events)		(0.298)	(0.814)	(0.731)	(0.261)	(0.002)
δ_{22} (Negative	0.214	0.757	0.533	0.358	1.273	-0.191
Rating Events)	(0.634)	(0.160)	(0.127)	(0.402)	(0.291)	(0.507)
λ_{21} (Positive		-0.568*	0.657**	0.001	-0.817**	-1.093
Rating Events)		(0.066)	(0.012)	(0.998)	(0.048)	(0.152)
λ_{22} (Negative	-0.189	-0.091	-0.143	0.193	-0.762***	0.685
Rating Events)	(0.513)	(0.755)	(0.312)	(0.422)	(0.004)	(0.205)
v_1 (Positive		0.715	-0.090	-0.692***	0.030	0.112
Rating Events)		(0.187)	(0.286)	(0.000)	(0.650)	(0.524)
v_2 (Negative	-0.025	0.593***	0.044	-0.686	0.375***	-0.128
Rating Events)	(0.672)	(0.000)	(0.424)	(0.170)	(0.000)	(0.179)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is positive rating events and $Event_{2t}$ is negative rating events.
GARCH:
$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + \lambda_{11}Positive\ Rating\ Events_t + \lambda_{12}Negative\ Rating\ Events_t$
$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + \lambda_{21}Positive\ Rating\ Events_t + \lambda_{22}Negative\ Rating\ Events_t$
GJR:
$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_{11}Positive\ Rating\ Events_t +$
$\lambda_{12}Negative\ Rating\ Events_t$
$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_{21}Positive\ Rating\ Events_t +$
$\lambda_{22}Negative\ Rating\ Events_t$
The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.9: Estimation Results of Domestic Sovereign Rating Surprises

	Austria	Cyprus (E)	France	Ireland	Italy (E)	Spain
δ_1 (Rating Surprises)	-2.162	-0.019***	-0.888	-2.314*	-1.604	0.497
	(0.379)	(0.001)	(0.904)	(0.058)	(0.734)	(0.728)
λ_1 (Rating Surprises)	-0.035	-1.388***	0.400	0.567*	0.084	-0.173
	(0.932)	(0.000)	(0.560)	(0.055)	(0.915)	(0.609)
δ_2 (Rating Surprises)	-0.600	-0.042	-0.571	0.076	-1.719	-0.292
	(0.380)	(0.480)	(0.684)	(0.844)	(0.575)	(0.657)
λ_2 (Rating Surprises)	0.312	0.229	-0.395	0.197	-0.170	-0.295
	(0.600)	(0.212)	(0.414)	(0.401)	(0.802)	(0.180)
v (Rating Surprises)	0.809***	0.262***	0.040	-0.070	0.204***	-0.050
	(0.000)	(0.000)	(0.857)	(0.593)	(0.006)	(0.144)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is rating surprises.

EGARCH without asymmetry (E):

$$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_1 Rating\ \text{Surprises}_t$$

$$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_2 Rating\ \text{Surprises}_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.10: Estimation Results of Bailout Events

	Portugal (GJR)	Spain	Italy	Ireland (GJR)	Cyprus (GJR)
δ_1(Bailout Events)	-4.781***	1.253***	1.997***	-1.339	3.412***
	(0.000)	(0.000)	(0.000)	(0.344)	(0.001)
λ_1(Bailout Events)	-0.985	0.591***	0.862***	2.229	7.329
	(0.846)	(0.009)	(0.000)	(0.407)	(0.205)
δ_2(Bailout Events)	-0.966**	-1.092	-1.297**	-0.423	-0.865
	(0.044)	(0.101)	(0.043)	(0.243)	(0.394)
λ_2(Bailout Events)	0.432	0.380***	0.355**	-0.079	4.605*
	(0.437)	(0.003)	(0.020)	(0.693)	(0.067)
v(Bailout Events)	-0.288***	-0.035*	-0.032	-0.563***	-0.204
	(0.003)	(0.062)	(0.175)	(0.000)	(0.219)
	Germany	France	Netherlands	Belgium (GJR)	Austria (GJR)
δ_1(Bailout Events)	2.000	0.603	0.456	-0.571	1.546
	(0.413)	(0.763)	(0.721)	(0.767)	(0.393)
λ_1(Bailout Events)	0.550*	0.331*	0.009	13.923*	11.255**
	(0.071)	(0.078)	(0.961)	(0.053)	(0.011)
δ_2(Bailout Events)	-0.779***	-0.839*	-0.606	-0.605	-0.329
	(0.000)	(0.075)	(0.115)	(0.191)	(0.426)
λ_2(Bailout Events)	0.158	0.144	0.126	0.414*	0.529*
	(0.239)	(0.242)	(0.320)	(0.092)	(0.049)
v(Bailout Events)	-0.087***	-0.112***	-0.119	-0.179***	-0.049
	(0.000)	(0.007)	(0.622)	(0.000)	(0.801)
	Slovenia (GJR)	Finland (GJR)	U.S. (GARCH)	U.K.	
δ_1(Bailout Events)	-0.553	-0.214	0.043	-0.611	
	(0.655)	(0.855)	(0.993)	(0.431)	
λ_1(Bailout Events)	6.650***	7.941**	14.671***	-3.079***	
	(0.001)	(0.032)	(0.000)	(0.000)	
δ_2(Bailout Events)	0.271	-0.913**	0.476	-0.631	
	(0.425)	(0.033)	(0.499)	(0.715)	
λ_2(Bailout Events)	0.398	-0.001	1.237	0.412	
	(0.407)	(0.997)	(0.220)	(0.372)	
v(Bailout Events)	-0.362*	-0.092**	-0.305***	-0.099***	
	(0.062)	(0.014)	(0.000)	(0.006)	

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is bailout events.

GJR:
$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_1 Bailout\ Events_t$
$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_2 Bailout\ Events_t$

GARCH:
$log\ h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + \lambda_1 Bailout\ Events_t$
$log\ h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + \lambda_2 Bailout\ Events_t$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.11: Estimation Results of Bailouts and Domestic Sovereign Rating Events

	Portugal (E)	Spain	Italy (GJR)	Ireland	Cyprus (E)
δ_{11} (Rating Events)	-0.925* (0.088)	0.045 (0.934)	-0.377 (0.567)	-1.166*** (0.000)	-0.364* (0.077)
δ_{12} (Bailout Events)	-4.849* (0.075)	1.250*** (0.000)	0.127 (0.956)	-1.708 (0.180)	1.853 (0.247)
λ_{11} (Rating Events)	-0.314*** (0.000)	-0.077 (0.386)	-0.061 (0.976)	0.196*** (0.000)	-0.393*** (0.000)
λ_{12} (Bailout Events)	1.217*** (0.000)	0.577** (0.011)	33.850** (0.029)	0.315* (0.071)	0.351 (0.301)
δ_{21} (Rating Events)	0.038 (0.749)	0.088 (0.588)	0.110 (0.691)	0.114 (0.305)	0.021 (0.702)
δ_{22} (Bailout Events)	-0.800 (0.135)	-1.097* (0.074)	-0.991* (0.091)	-0.518*** (0.000)	-1.130 (0.213)
λ_{21} (Rating Events)	-0.033 (0.616)	-0.002 (0.971)	-0.202 (0.438)	0.043 (0.491)	0.045 (0.334)
λ_{22} (Bailout Events)	0.438** (0.015)	0.382*** (0.005)	1.407** (0.040)	0.012 (0.945)	0.449*** (0.005)
υ_1 (Rating Events)	0.045 (0.274)	0.005*** (0.000)	0.019** (0.015)	-0.050 (0.246)	-0.022 (0.726)
υ_2 (Bailout Events)	-0.458*** (0.000)	-0.024 (0.180)	-0.020 (0.342)	-0.330** (0.023)	-0.137 (0.414)
	Germany	France	Netherlands (GARCH)	Belgium	Austria
δ_{11} (Rating Events)	2.705 (0.573)	0.015 (0.994)	0.061 (0.966)	0.447*** (0.000)	-1.210 (0.307)
δ_{12} (Bailout Events)	-0.674 (0.801)	0.603 (0.772)	0.588 (0.579)	-0.672*** (0.000)	0.522 (0.772)
λ_{11} (Rating Events)	-0.131 (0.895)	0.056 (0.809)	0.568 (0.867)	-0.208 (0.213)	0.477*** (0.006)
λ_{12} (Bailout Events)	0.565* (0.063)	0.327 (0.102)	-0.749 (0.771)	0.488** (0.030)	0.369*** (0.004)
δ_{21} (Rating Events)	1.760* (0.057)	0.171 (0.706)	0.144 (0.722)	0.091 (0.669)	-0.369 (0.318)
δ_{22} (Bailout Events)	-0.778*** (0.000)	-0.839* (0.050)	-0.441 (0.306)	-0.496 (0.232)	-0.421 (0.360)
λ_{21} (Rating Events)	-0.142 (0.707)	-0.090 (0.505)	-0.219 (0.445)	0.038 (0.720)	-0.238 (0.260)
λ_{22} (Bailout Events)	0.147 (0.250)	0.148 (0.262)	0.585* (0.057)	0.200 (0.152)	0.347** (0.014)
υ_1 (Rating Events)	-0.104 (0.335)	-0.007 (0.905)	0.654*** (0.000)	0.068 (0.303)	0.223*** (0.000)
υ_2 (Bailout Events)	-0.090*** (0.000)	-0.109** (0.014)	-0.084 (0.703)	-0.252*** (0.000)	-0.070*** (0.000)
	Slovenia	Finland (E)	U.S.	U.K. (E)	
δ_{11} (Rating Events)	0.162 (0.530)	0.218 (0.684)	-0.971 (0.574)	-0.070 (0.848)	
δ_{12} (Bailout Events)	-0.967 (0.146)	-0.278 ()0.788	-4.298 (0.560)	-1.705*** (0.000)	
λ_{11} (Rating Events)	0.086** (0.043)	0.894** (0.017)	0.310 (0.427)	3.765*** (0.000)	
λ_{12} (Bailout Events)	0.219** (0.018)	0.468** (0.040)	3.065*** (0.000)	0.425 (0.662)	
δ_{21} (Rating Events)	-0.072 (0.456)	0.298 (0.483)	0.423 (0.188)	-0.566 (0.132)	

δ_{22} (Bailout Events)	0.127	-0.956**	0.593	-1.344
	(0.671)	(0.027)	(0.422)	(0.455)
λ_{21} (Rating Events)	0.109	0.059	-0.754***	0.117
	(0.486)	(0.817)	(0.001)	(0.816)
λ_{22} (Bailout Events)	-0.037	0.241*	0.674***	0.879*
	(0.897)	(0.052)	(0.001)	(0.077)
v_1 (Rating Events)	-0.023	0.120**	0.032	0.190
	(0.578)	(0.020)	(0.725)	(0.742)
v_2 (Bailout Events)	-0.257***	-0.108***	-0.371***	-0.809***
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is rating events and $Event_{2t}$ is bailout events.

GARCH:

$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + \lambda_{11} RatingEvents_t + \lambda_{12} BailoutEvents_t$

$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + \lambda_{21} RatingEvents_t + \lambda_{22} BailoutEvents_t$

GJR:

$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_{11} RatingEvents_t + \lambda_{12} BailoutEvents_t$

$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_{21} RatingEvents_t + \lambda_{22} BailoutEvents_t$

EGARCH without asymmetry (E):

$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_{11} RatingEvents_t + \lambda_{12} BailoutEvents_t$

$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_{21} RatingEvents_t + \lambda_{22} BailoutEvents_t$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.12: Estimation Results of Spillover Effect of Greek Sovereign Rating Events

	Portugal	Spain	Italy	Ireland (ET)	Cyprus
δ_{11} (Domestic	-0.854*	0.095***	-0.421	-0.703***	-0.503*
Rating Events)	(0.071)	(0.003)	(0.497)	(0.000)	(0.057)
δ_{12} (Greek	-0.262***	-0.123	-0.083	-0.260***	-0.050***
Rating Events)	(0.000)	(0.592)	(0.734)	(0.001)	(0.000)
δ_{13} (Bailout	-4.332***	0.466	1.981***	-1.360	1.441***
Events)	(0.000)	(0.846)	(0.000)	(0.162)	(0.000)
λ_{11} (Domestic	-0.306***	-0.059	0.019	0.151	-0.311***
Rating Events)	(0.000)	(0.504)	(0.863)	(0.262)	(0.000)
λ_{12} (Greek	-0.024	-0.221***	-0.184***	-0.236***	-0.327**
Rating Events)	(0.700)	(0.000)	(0.001)	(0.001)	(0.016)
λ_{13} (Bailout	1.080***	0.533**	0.818***	0.686**	0.373
Events)	(0.000)	(0.038)	(0.001)	(0.030)	(0.302)
δ_{21} (Domestic	0.024	0.068	0.307	0.064	0.020
Rating Events)	(0.802)	(0.642)	(0.299)	(0.524)	(0.743)
δ_{22} (Greek	0.088	0.213**	0.200**	0.078	0.032
Rating Events)	(0.301)	(0.017)	(0.029)	(0.234)	(0.794)
δ_{23} (Bailout	-1.057*	-1.112*	-1.287*	-0.555	-1.093
Events)	(0.059)	(0.072)	(0.055)	(0.110)	(0.238)
λ_{21} (Domestic	0.013	-0.001	-0.100	0.098	0.044
Rating Events)	(0.841)	(0.982)	(0.147)	(0.129)	(0.417)
λ_{22} (Greek	-0.056	-0.023	0.003	-0.070*	0.024
Rating Events)	(0.267)	(0.435)	(0.924)	(0.079)	(0.608)
λ_{23} (Bailout	0.346*	0.367***	0.378**	0.055	0.471**
Events)	(0.093)	(0.008)	(0.013)	(0.758)	(0.014)
v_1 (Domestic	0.065**	0.002	0.011	-0.005***	-0.082
Rating Events)	(0.031)	(0.784)	(0.257)	(0.000)	(0.173)
v_2 (Greek	0.045*	0.007	0.007	0.001	0.022
Rating Events)	(0.063)	(0.121)	(0.277)	(0.544)	(0.686)
v_3 (Bailout	-0.403***	0.005	-0.002	-0.001	-0.093
Events)	(0.000)	(0.872)	(0.957)	(0.932)	(0.598)

	Germany (E)	France	Netherlands	Belgium	Austria
δ_{11} (Domestic	2.399	-0.049	-0.229	0.459***	-1.150
Rating Events)	(0.559)	(0.980)	(0.796)	(0.000)	(0.362)
δ_{12} (Greek	-0.184	-0.209	-0.002	-0.058	-0.044
Rating Events)	(0.497)	(0.329)	(0.905)	(0.816)	(0.841)
δ_{13} (Bailout	2.203	0.607	0.425	-0.692***	0.884
Events)	(0.349)	(0.750)	(0.735)	(0.000)	(0.649)
λ_{11} (Domestic	-0.192	0.055	0.271	-0.179	0.491***
Rating Events)	(0.854)	(0.804)	(0.432)	(0.421)	(0.001)
λ_{12} (Greek	-0.233***	-0.022	-0.034	-0.205***	-0.126***
Rating Events)	(0.000)	(0.653)	(0.454)	(0.000)	(0.000)
λ_{13} (Bailout	0.463*	0.297	-0.022	0.458**	0.195*
Events)	(0.098)	(0.113)	(0.898)	(0.029)	(0.072)
δ_{21} (Domestic	1.852	0.192	0.116	0.091	-0.369
Rating Events)	(0.136)	(0.685)	(0.723)	(0.664)	(0.289)
δ_{22} (Greek	0.129*	0.141**	0.105*	0.116*	0.075
Rating Events)	(0.057)	(0.048)	(0.089)	(0.061)	(0.254)
δ_{23} (Bailout	-0.676	-0.842*	-0.621*	-0.499	-0.424
Events)	(0.137)	(0.074)	(0.098)	(0.193)	(0.316)
λ_{21} (Domestic	0.012	-0.102	-0.307	0.044	-0.235
Rating Events)	(0.980)	(0.409)	(0.180)	(0.688)	(0.227)
λ_{22} (Greek	-0.012	-0.021	-0.011	-0.029	-0.014
Rating Events)	(0.748)	(0.543)	(0.723)	(0.408)	(0.687)
λ_{23} (Bailout	0.250*	0.149	0.113	0.192	0.340**
Events)	(0.099)	(0.253)	(0.382)	(0.164)	(0.023)

v_1 (Domestic	0.185	-0.029**	0.742***	0.070	0.222***
Rating Events)	(0.155)	(0.040)	(0.000)	(0.273)	(0.000)
v_2 (Greek	0.019***	0.015***	0.016	0.024**	-0.001
Rating Events)	(0.000)	(0.000)	(0.784)	(0.048)	(0.884)
v_3 (Bailout	0.027	0.016	-0.101	-0.226***	-0.074**
Events)	(0.433)	(0.401)	(0.648)	(0.002)	(0.043)
	Slovenia (E)	U.S.	U.K.		
δ_{11} (Domestic	0.179	-0.894	-0.129		
Rating Events)	(0.361)	(0.695)	(0.756)		
δ_{12} (Greek	-0.235**	-0.062***	-0.355***		
Rating Events)	(0.019)	(0.000)	(0.000)		
δ_{13} (Bailout	-0.903***	1.345	-1.697***		
Events)	(0.000)	(0.790)	(0.000)		
λ_{11} (Domestic	0.067	0.314	3.920***		
Rating Events)	(0.124)	(0.434)	(0.000)		
λ_{12} (Greek	-0.069***	0.056	0.011		
Rating Events)	(0.004)	(0.339)	(0.902)		
λ_{13} (Bailout	0.158	3.061***	0.460		
Events)	(0.145)	(0.000)	(0.526)		
δ_{21} (Domestic	-0.055	0.419	-0.592*		
Rating Events)	(0.605)	(0.165)	(0.077)		
δ_{22} (Greek	0.021	0.166***	0.075		
Rating Events)	(0.659)	(0.002)	(0.158)		
δ_{23} (Bailout	0.083**	0.593	-0.626		
Events)	(0.045)	(0.437)	(0.713)		
λ_{21} (Domestic	0.052	-0.766***	-0.014		
Rating Events)	(0.720)	(0.001)	(0.969)		
λ_{22} (Greek	0.156**	-0.051	0.027		
Rating Events)	(0.039)	(0.105)	(0.453)		
λ_{23} (Bailout	0.005	0.680***	0.386		
Events)	(0.987)	(0.001)	(0.386)		
v_1 (Domestic	0.010	0.206***	0.010		
Rating Events)	(0.945)	(0.000)	(0.838)		
v_2 (Greek	-0.071	0.040***	0.011***		
Rating Events)	(0.179)	(0.000)	(0.000)		
v_3 (Bailout	-0.276	-0.373***	-0.104***		
Events)	(0.189)	(0.000)	(0.001)		

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is domestic rating events, $Event_{2t}$ is Greek rating events, and $Event_{3t}$ is bailout events.

EGARCH without asymmetry (E):

$$log\, h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\, log\, h_{1t-1} + \lambda_{11} Domestic\ Rating\ Events_t + \lambda_{12} Greece\ Rating\ Events_t + \lambda_{13} Bailout\ Events_t$$

$$log\, h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\, log\, h_{2t-1} + \lambda_{21} Domestic\ Rating\ Events_t + \lambda_{22} Greece\ Rating\ Events_t + \lambda_{23} Bailout\ Events_t$$

ET denotes Student's t EGARCH without asymmetry. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.13: Linear Regression Results of Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
ϕ_1 (Rating Events)	0.004	0.038***	0.065***	0.000	0.005
	(0.473)	(0.000)	(0.003)	(0.960)	(0.308)
	Germany	France	Netherlands	Belgium	Austria
ϕ_1 (Rating Events)	0.046	0.149**	0.157***	0.084***	0.011
	(0.702)	(0.012)	(0.009)	(0.007)	(0.432)
	Slovenia	Finland	U.S.	U.K.	
ϕ_1 (Rating Events)	-0.013	0.005	0.041	0.143***	
	(0.408)	(0.187)	(0.132)	(0.000)	

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 Rating\ Event_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.14: Linear Regression Results of Domestic Negative and Positive Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
ϕ_1 (Positive Rating Events)	-0.008	-0.007	-0.053	0.019	0.012
	(0.647)	(0.833)	(0.608)	(0.160)	(0.406)
ϕ_2 (Negative Rating Events)	0.005	0.045***	0.073***	-0.003	0.001
	(0.322)	(0.000)	(0.002)	(0.572)	(0.338)
	Germany	France	Netherlands	Belgium	Finland
ϕ_1 (Positive Rating Events)	-0.450***		0.109***	-0.021	-0.014***
	(0.000)		(0.000)	(0.814)	(0.000)
ϕ_2 (Negative Rating Events)	0.145	0.142**	0.211*	0.103***	0.012***
	(0.211)	(0.013)	(0.077)	(0.001)	(0.000)
	U.S.	U.K.			
ϕ_1 (Positive Rating Events)	0.040	0.181***			
	(0.548)	(0.000)			
ϕ_2 (Negative Rating Events)	0.049***	0.124***			
	(0.000)	(0.000)			

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 Positive\ Rating\ Event_t + \phi_2 Negative\ Rating\ Event_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.15: Linear Regression Results of Domestic Sovereign Rating Surprises

	Austria	Cyprus	France	Ireland	Italy	Spain
ϕ_1 (Rating Surprises)	-0.014***	-0.001	0.289***	0.015***	0.089***	0.029
	(0.000)	(0.338)	(0.000)	(0.000)	(0.000)	(0.294)

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 Rating\ Surprises_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.16: Linear Regression Results of Bailouts Events

	Portugal	Spain	Italy	Ireland	Cyprus
ϕ_1 (Bailout Events)	-0.082**	-0.041	-0.036	-0.023	-0.008***
	(0.010)	(0.236)	(0.528)	(0.360)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
ϕ_1 (Bailout Events)	-0.035**	-0.050***	-0.066	-0.122***	0.021*
	(0.032)	(0.004)	(0.161)	(0.001)	(0.053)
	Slovenia	Finland	U.S.	U.K.	
ϕ_1 (Bailout Events)	-0.018	0.005	-0.039	0.039***	
	(0.425)	(0.511)	(0.226)	(0.000)	

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 Bailout\ Events_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.17: Linear Regression Results of Bailouts and Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
ϕ_1 (Rating Events)	0.006	0.038***	0.070***	-0.001	0.004
	(0.379)	(0.000)	(0.002)	(0.929)	(0.288)
ϕ_2 (Bailout Events)	-0.061**	-0.044	-0.040	-0.019	-0.007***
	(0.011)	(0.205)	(0.507)	(0.405)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
ϕ_1 (Rating Events)	0.045	0.150**	0.112***	0.087***	0.008
	(0.706)	(0.011)	(0.007)	(0.005)	(0.435)
ϕ_2 (Bailout Events)	-0.035**	-0.051***	-0.062*	-0.118***	0.026**
	(0.024)	(0.003)	(0.056)	(0.002)	(0.038)
	Slovenia	Finland	U.S.	U.K.	
ϕ_1 (Rating Events)	-0.013	0.006	0.046	-0.008	
	(0.355)	(0.352)	(0.127)	(0.376)	
ϕ_2 (Bailout Events)	-0.008	0.005	-0.043*	-0.076***	
	(0.634)	(0.496)	(0.079)	(0.000)	

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 RatingEvents + \phi_2 BailoutEvents_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.18: Linear Regression Results of Spillover Effect of Greek Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
ϕ_1 (Domestic	0.001	0.037***	0.065***	-0.003	0.005
Rating Events)	(0.795)	(0.000)	(0.002)	(0.451)	(0.297)
ϕ_2 (Greek Rating	0.000	-0.018***	-0.033***	-0.002	-0.005
Events)	(0.867)	(0.003)	(0.000)	(0.611)	(0.185)
ϕ_3 (Bailout Events)	-0.021*	-0.037	-0.028	-0.007	-0.009***
	(0.061)	(0.300)	(0.622)	(0.848)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
ϕ_1 (Domestic	0.030	0.150**	0.158***	0.086***	0.004
Rating Events)	(0.798)	(0.011)	(0.007)	(0.005)	(0.425)
ϕ_2 (Greek Rating	-0.001	-0.002	-0.019**	0.004	-0.002
Events)	(0.942)	(0.818)	(0.039)	(0.689)	(0.371)
ϕ_3 (Bailout Events)	-0.028*	-0.051***	-0.066	-0.102***	0.017**
	(0.066)	(0.003)	(0.168)	(0.005)	(0.036)
	Slovenia	U.S.	U.K.		
ϕ_1 (Domestic	-0.013	0.025	-0.016**		
Rating Events)	(0.379)	(0.299)	(0.018)		
ϕ_2 (Greek Rating	-0.003	-0.004	0.007*		
Events)	(0.450)	(0.503)	(0.064)		
ϕ_3 (Bailout Events)	-0.005	-0.037*	-0.062***		
	(0.789)	(0.090)	(0.000)		

Notes: This table reports the key estimation results of the following equation:

$$\widetilde{\rho_{12t}} = \xi_0 + \phi_1 Domestic\ Rating\ Events + \phi_2 Greece\ Rating\ Events_t + \phi_3 Bailout\ Events_t + u_t \tag{4.10}$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.19: Estimation Results of Domestic Sovereign Rating Events – Sy's (2004) CCR Coding Method

	Portugal	Spain	Italy	Ireland	Cyprus
δ_1 (Rating Events)	-0.090	0.059	0.254	-0.486***	-0.057
	(0.685)	(0.729)	(0.322)	(0.000)	(0.617)
λ_1 (Rating Events)	-0.148***	-0.015	0.020	0.077***	-0.077*
	(0.000)	(0.614)	(0.665)	(0.000)	(0.052)
δ_2 (Rating Events)	-0.018	0.023	0.048	0.054	-0.000
	(0.726)	(0.763)	(0.722)	(0.202)	(0.998)
λ_2 (Rating Events)	0.003	-0.022	-0.041	0.025	0.012
	(0.924)	(0.273)	(0.183)	(0.241)	(0.555)
v (Rating Events)	0.031***	0.003	0.009**	-0.020*	-0.012
	(0.004)	(0.271)	(0.010)	(0.075)	(0.676)
	Germany (GJR)	France (GARCH)	Netherlands	Belgium	Austria (E)
δ_1 (Rating Events)	0.605	0.160	-0.311	0.229***	-0.366
	(0.509)	(0.723)	(0.783)	(0.000)	(0.371)
λ_1 (Rating Events)	7.446**	2.219***	0.478***	0.057	0.318***
	(0.020)	(0.000)	(0.009)	(0.638)	(0.000)
δ_2 (Rating Events)	0.382	0.151	0.014	0.058	-0.207
	(0.460)	(0.390)	(0.954)	(0.726)	(0.180)
λ_2 (Rating Events)	-0.756*	0.093	-0.123	0.024	0.160*
	(0.075)	(0.479)	(0.406)	(0.695)	(0.071)
v (Rating Events)	0.069	-0.011	0.002	0.020	0.221***
	(0.468)	(0.850)	(0.972)	(0.534)	(0.000)
	Slovenia (GJR)	Finland	U.S.	U.K. (EAT)	
δ_1 (Rating Events)	-0.206	0.840	-2.300***	0.468	
	(0.121)	(0.167)	(0.000)	(0.460)	
λ_1 (Rating Events)	-0.318**	-0.399*	-0.214	-0.226	
	(0.015)	(0.056)	(0.372)	(0.847)	
δ_2 (Rating Events)	-0.055	0.171	0.472***	-0.508*	
	(0.209)	(0.517)	(0.000)	(0.097)	
λ_2 (Rating Events)	0.023	0.065	-0.540***	0.291	
	(0.616)	(0.607)	(0.004)	(0.419)	
v (Rating Events)	0.011	0.320***	0.236***	-0.065***	
	(0.676)	(0.000)	(0.000)	(0.002)	

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is rating events. Sy's (2004) CCR coding method is used.

GARCH:
$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + \lambda_1 Rating\ Events_t$
$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + \lambda_2 Rating\ Events_t$

GJR:
$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_1 Rating\ Events_t$
$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_2 Rating\ Events_t$

EGARCH without asymmetry (E):
$log\ h_{1t} = c_1 + a_1\frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_1 Rating\ Events_t$
$log\ h_{2t} = c_2 + a_2\frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_2 Rating\ Events_t$

EAT denotes Student's t-EGARCH with asymmetry and ET denotes Student's t-EGARCH without asymmetry. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.20: Estimation Results of Domestic Positive and Negative Sovereign Rating Events – Sy's (2004) CCR Coding Method

	Portugal	Spain	Italy	Ireland	Cyprus (E)
δ_{11} (Positive Rating Events)	0.026*** (0.000)	0.015 (0.975)	-1.823 (0.239)	-0.719** (0.018)	-0.007*** (0.000)
δ_{12} (Negative Rating Events)	-0.618** (0.016)	0.085 (0.642)	0.287 (0.268)	-0.364** (0.010)	-0.250*** (0.000)
λ_{11} (Positive Rating Events)	-0.784*** (0.000)	0.007 (0.945)	-0.362 (0.448)	0.290*** (0.000)	-0.301*** (0.000)
λ_{12} (Negative Rating Events)	-0.126*** (0.000)	-0.017 (0.572)	0.022 (0.622)	0.024 (0.377)	0.044*** (0.000)
δ_{21} (Positive Rating Events)	-0.233 (0.286)	-0.064 (0.638)	0.202 (0.821)	0.035 (0.693)	0.007 (0.810)
δ_{22} (Negative Rating Events)	0.004 (0.943)	0.055 (0.514)	0.043 (0.750)	0.056 (0.164)	-0.011 (0.549)
λ_{21} (Positive Rating Events)	0.144 (0.195)	-0.128* (0.064)	0.110 (0.782)	-0.067 (0.252)	0.035 (0.241)
λ_{22} (Negative Rating Events)	-0.010 (0.720)	-0.015 (0.465)	-0.042 (0.187)	0.039* (0.076)	0.006 (0.749)
v_1 (Positive Rating Events)	0.158** (0.035)	-0.019* (0.075)	-0.081 (0.119)	-0.045* (0.095)	0.094*** (0.000)
v_2 (Negative Rating Events)	0.025 (0.110)	0.006* (0.056)	0.010*** (0.004)	-0.024 (0.127)	-0.031** (0.026)
	Germany	**France (E)**	**Belgium**	**Finland**	**U.K.**
δ_{11} (Positive Rating Events)			0.872 (0.159)	0.813 (0.330)	-3.233 (0.846)
δ_{12} (Negative Rating Events)	0.675 (0.565)	0.299*** (0.000)	0.232*** (0.000)	0.895 (0.211)	0.948 (0.235)
λ_{11} (Positive Rating Events)			-1.241*** (0.002)	-1.164** (0.022)	2.694** (0.046)
λ_{12} (Negative Rating Events)	0.387 (0.206)	0.209** (0.037)	0.181 (0.150)	-0.248 (0.354)	2.059*** (0.004)
δ_{21} (Positive Rating Events)			-0.174 (0.692)	-0.389 (0.508)	-0.910*** (0.002)
δ_{22} (Negative Rating Events)	0.303*** (0.000)	0.184*** (0.000)	0.119 (0.586)	0.330 (0.254)	-0.280 (0.322)
λ_{21} (Positive Rating Events)			0.747*** (0.004)	0.096 (0.691)	-1.095 (0.124)
λ_{22} (Negative Rating Events)	-0.237 (0.142)	0.063 (0.407)	0.002 (0.980)	0.056 (0.659)	0.620* (0.095)
v_1 (Positive Rating Events)			-0.090 (0.331)	0.443 (0.375)	0.244*** (0.001)
v_2 (Negative Rating Events)	0.083 (0.325)	-0.016 (0.779)	0.018 (0.571)	0.315*** (0.000)	-0.155*** (0.000)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is positive rating events and $Event_{2t}$ is negative rating events. Sy's (2004) CCR coding method is used. EGARCH without asymmetry (E):

$$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_{11} Positive\ Rating\ Events_t + \lambda_{12} Negative\ Rating\ Events_t$$

$$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_{21} Positive\ Rating\ Events_t + \lambda_{22} Negative\ Rating\ Events_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.21: Estimation Results of Bailouts and Domestic Sovereign Rating Events – Sy's (2004) CCR Coding Method

	Portugal	Spain	Italy	Ireland (GJR)	Germany	France (EAT)
δ_{11}(Rating Events)	-0.073 (0.707)	0.100 (0.547)	0.255 (0.280)	-0.544*** (0.000)	0.649 (0.541)	0.165 (0.545)
δ_{12} (Bailout Events)	-4.329*** (0.000)	1.252*** (0.000)	1.998*** (0.000)	-1.304 (0.378)	1.971 (0.457)	0.470 (0.758)
(Rating Events)	-0.141*** (0.001)	0.003 (0.929)	0.007 (0.897)	0.523*** (0.000)	0.398 (0.218)	-0.240 (0.122)
λ_{12} (Bailout Events)	1.012*** (0.000)	0.601** (0.010)	0.859*** (0.000)	3.477 (0.233)	0.552* (0.055)	1.018*** (0.000)
δ_{21} (Rating Events)	-0.010 (0.826)	0.025 (0.720)	0.048 (0.749)	0.054 (0.124)	0.305*** (0.000)	0.133 (0.408)
δ_{22} (Bailout Events)	-1.042** (0.048)	-1.087* (0.084)	-1.307* (0.073)	-0.407 (0.260)	-0.779*** (0.000)	-0.987** (0.020)
λ_{21} (Rating Events)	0.010 (0.690)	-0.005 (0.769)	-0.044 (0.173)	0.041*** (0.002)	-0.241* (0.080)	0.039 (0.642)
λ_{22} (Bailout Events)	0.388** (0.034)	0.371*** (0.006)	0.363** (0.015)	-0.048 (0.806)	0.157 (0.236)	0.128 (0.452)
v_1 (Rating Events)	0.030*** (0.006)	-0.000 (0.971)	0.008** (0.018)	-0.027** (0.017)	-0.053* (0.066)	-0.080 (0.739)
v_2 (Bailout Events)	-0.408*** (0.000)	-0.035 (0.183)	-0.028 (0.232)	-0.279*** (0.003)	-0.073*** (0.001)	0.025 (0.957)

	Netherlands	Belgium (ET)	Austria (E)	Finland	U.K.
δ_{11}(Rating Events)	-0.311 (0.574)	0.244 (0.445)	-0.371 (0.346)	0.820 (0.195)	0.768 (0.342)
δ_{12} (Bailout Events)	0.408 (0.738)	-0.590 (0.674)	0.483 (0.801)	-0.346 (0.697)	-0.586 (0.431)
(Rating Events)	0.478*** (0.006)	0.023 (0.878)	0.300*** (0.000)	-0.413** (0.038)	2.150** (0.015)
λ_{12} (Bailout Events)	-0.003 (0.985)	1.135*** (0.000)	0.333*** (0.002)	0.531** (0.017)	-3.112*** (0.000)
δ_{21} (Rating Events)	0.013 (0.957)	0.028 (0.855)	-0.205 (0.185)	0.169 (0.471)	-0.608** (0.033)
δ_{22} (Bailout Events)	-0.610 (0.138)	-0.641 (0.133)	-0.363 (0.410)	-0.934** (0.040)	-0.627 (0.712)
λ_{21} (Rating Events)	-0.123 (0.412)	0.068 (0.481)	0.122 (0.145)	0.073 (0.551)	0.133 (0.686)
λ_{22} (Bailout Events)	0.120 (0.352)	0.304 (0.145)	0.462*** (0.000)	0.022 (0.841)	0.397 (0.382)
v_1 (Rating Events)	-0.001 (0.985)	-0.013*** (0.000)	0.222*** (0.000)	0.077*** (0.009)	-0.043 (0.170)
v_2 (Bailout Events)	-0.064* (0.064)	0.008 (0.687)	-0.154 (0.428)	-0.111*** (0.000)	-0.093*** (0.007)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is rating events and $Event_{2t}$ is bailout events. Sy's (2004) CCR coding method is used.
EGARCH without asymmetry (E):

$$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_{11} RatingEvents_t + \lambda_{12} BailoutEvents_t$$

$$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_{21} RatingEvents_t + \lambda_{22} BailoutEvents_t$$

EAT denotes Student's t-EGARCH with asymmetry and ET denotes Student's t-EGARCH without asymmetry. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4.22: Estimation Results of Spillover Effect of Greek Sovereign Rating Events – Sy's (2004) CCR Coding Method

	Portugal (EAT)	Spain	Italy	Ireland	Germany (ET)
δ_{11} (Domestic Rating Events)	0.002***	0.106	0.246	-0.481***	2.033***
	(0.000)	(0.507)	(0.483)	(0.000)	(0.000)
δ_{12} (Greek Rating Events)	-0.035	-0.106	-0.080	-0.100**	0.004
	(0.361)	(0.248)	(0.308)	(0.048)	(0.737)
δ_{13} (Bailout Events)	-3.347***	0.369	1.974***	-1.733	0.110
	(0.006)	(0.865)	(0.000)	(0.285)	(0.916)
λ_{11} (Domestic Rating Events)	-0.093**	0.007	0.004	0.082***	3.845***
	(0.017)	(0.837)	(0.960)	(0.000)	(0.000)
λ_{12} (Greek Rating Events)	-0.031	-0.066***	-0.064***	-0.005	-0.044***
	(0.199)	(0.001)	(0.004)	(0.728)	(0.001)
λ_{13} (Bailout Events)	0.745**	0.622**	0.846***	0.306	0.299**
	(0.017)	(0.010)	(0.008)	(0.102)	(0.022)
δ_{21} (Domestic Rating Events)	-0.014	0.019	0.040	0.054	0.197
	(0.787)	(0.788)	(0.773)	(0.192)	(0.645)
δ_{22} (Greek Rating Events)	0.032	0.079***	0.082**	0.050**	0.045**
	(0.257)	(0.004)	(0.010)	(0.048)	(0.025)
δ_{23} (Bailout Events)	-1.093**	-1.084*	-1.296*	-0.522	-0.760*
	(0.034)	(0.086)	(0.056)	(0.143)	(0.086)
λ_{21} (Domestic Rating Events)	0.015	-0.005	-0.045	0.026	0.054
	(0.588)	(0.779)	(0.156)	(0.207)	(0.805)
λ_{22} (Greek Rating Events)	-0.023	-0.005	-0.001	-0.022*	-0.012
	(0.186)	(0.700)	(0.913)	(0.099)	(0.493)
λ_{23} (Bailout Events)	0.318	0.370***	0.378**	-0.002	0.253
	(0.109)	(0.009)	(0.012)	(0.988)	(0.188)
v_1 (Domestic Rating Events)	0.001	-0.000	0.002	-0.023**	-0.019
	(0.795)	(0.828)	(0.648)	(0.017)	(0.124)
v_2 (Greek Rating Events)	-0.001	0.004***	0.005**	-0.001	-0.016***
	(0.673)	(0.008)	(0.019)	(0.828)	(0.000)
v_3 (Bailout Events)	0.025	0.017	0.010	-0.296***	-0.043
	(0.489)	(0.538)	(0.648)	(0.001)	(0.698)

	Belgium (E)	Austria (E)	U.S.	U.K.
δ_{11} (Domestic Rating Events)	0.240***	-0.344	-2.886***	0.771
	(0.000)	(0.363)	(0.000)	(0.353)
δ_{12} (Greek Rating Events)	-0.128	-0.155	-0.052***	-0.042***
	(0.183)	(0.130)	(0.000)	(0.000)
δ_{13} (Bailout Events)	-0.741***	0.686	1.263	-0.604
	(0.000)	(0.707)	(0.755)	(0.409)
λ_{11} (Domestic Rating Events)	0.039	0.310***	-0.208	2.149**
	(0.742)	(0.000)	(0.384)	(0.015)
λ_{12} (Greek Rating Events)	-0.052**	-0.039***	0.079***	-0.070*
	(0.021)	(0.000)	(0.000)	(0.070)
λ_{13} (Bailout Events)	0.422**	0.227**	2.984***	-3.097***
	(0.027)	(0.030)	(0.000)	(0.000)
δ_{21} (Domestic Rating Events)	0.035	-0.206	0.468***	-0.578*
	(0.837)	(0.181)	(0.000)	(0.059)
δ_{22} (Greek Rating Events)	0.042*	0.022	0.056***	0.027
	(0.052)	(0.324)	(0.001)	(0.109)
δ_{23} (Bailout Events)	-0.512	-0.357	0.596	-0.625
	(0.239)	(0.418)	(0.289)	(0.716)
λ_{21} (Domestic Rating Events)	0.057	0.127	-0.549***	0.125
	(0.468)	(0.134)	(0.001)	(0.706)

λ_{22} (Greek Rating Events)	-0.021	-0.003	-0.014	0.009
	(0.102)	(0.792)	(0.203)	(0.466)
λ_{23} (Bailout Events)	0.361**	0.456***	0.691***	0.388
	(0.016)	(0.001)	(0.001)	(0.392)
v_1 (Domestic Rating Events)	0.054*	0.218***	0.272***	0.001
	(0.059)	(0.000)	(0.000)	(0.979)
v_2 (Greek Rating Events)	0.004	-0.011	-0.001	0.004***
	(0.443)	(0.626)	(0.818)	(0.002)
v_3 (Bailout Events)	-0.264***	-0.115	-0.383***	-0.098***
	(0.000)	(0.539)	(0.000)	(0.002)

Notes: This table reports the estimation of key parameters in equations (4.1) – (4.6), when $Event_{1t}$ is domestic rating events, $Event_{2t}$ is Greek rating events, and $Event_{3t}$ is bailout events. Sy's (2004) CCR coding method is used.

EGARCH without asymmetry (E):

$$log\, h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\, log\, h_{1t-1} + \lambda_{11} Domestic\ Rating\ Events_t + \lambda_{12} Greece\ Rating\ Events_t + \lambda_{13} Bailout\ Events_t$$

$$log\, h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\, log\, h_{2t-1} + \lambda_{21} Domestic\ Rating\ Events_t + \lambda_{22} Greece\ Rating\ Events_t + \lambda_{23} Bailout\ Events_t$$

ET denotes Student's t EGARCH without asymmetry. EAT denotes Student's t EGARCH with asymmetry. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Appendix 4A: Major Bailouts in the U.S., the U.K., and the Eurozone

Table 4A: Major Bailouts in the U.S., the U.K., and the Eurozone

Major Bailouts in the U.S.	
The Emergency Economic Stabilization Act of 2008 (3/10/2008)	It is referred to as a bailout of the U.S. financial system. It is a law enacted to address the subprime mortgage crisis. It authorises the United States Secretary of the Treasury to use $700 billion to buy distressed assets, especially mortgage-backed securities, and provide cash directly to banks.
Bear Stearns (24/03/2008)	The Federal Reserve Bank of New York announced that it will provide financing support to help J.P. Morgan's acquisition of the Bear Stearns. Maiden Lane was formed to control $30 billion of the Bear Stearns assets. J.P. Morgan assumed the first $1 billion of any losses on the portfolio.
Fannie Mae and Freddie Mac (7/09/2008, 18/02/2009, 24/12/2009)	In 2008, the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in government conservatorship. In 2009, the U.S. Treasury Department raised its preferred stock purchase agreements with Fannie Mae and Freddie Mac to $200 billion and increased the limits on the size of Fannie Mae and Freddie Mac's portfolios to $900 billion. The U.S. Treasury Department announced the removal of caps on the amount of preferred stock that the Treasury may purchase in Fannie Mae and Freddie Mac to ensure that each firm maintains a positive net worth.
AIG (16/09/2008, 2/03/2009, 25/06/2009)	The Federal Reserve Board authorised the Federal Reserve Bank of New York to lend up to $85 billion to the American International Group (AIG) under Section 13(3) of the Federal Reserve Act. The U.S. Treasury Department and Federal Reserve Board announced a restructuring of the government's assistance to the AIG. The AIG announced that it has entered into an agreement with the Federal Reserve Bank of New York to reduce the debt the AIG owes the Federal Reserve Bank of New York by $25 billion.
Major Bailouts in the U.K.	
The second rescue package (19/01/2009)	Based on the first rescue package announced by the HM Treasury on 08/10/2008, the U.K. government announced a second rescue package for the U.K. banks. It includes the asset-based securities guarantee scheme and the asset protection scheme.
Special Resolution Regime (21/02/2009)	The Banking Act 2009 introduced a special resolution regime (SRR) giving power to the HM Treasury, the Bank of England and the Financial Services Authority to deal with distressed banks and building societies.

Table 4A: Major Bailouts in the U.S., the U.K., and the Eurozone (Continued)

Major Bailouts in the Eurozone	
The European Financial Stability Facility (EFSF) (09/05/2010, 10/05/2010)	The EU finance chiefs, in a 14-hour overnight session in Brussels, agreed to set up a 750 billion-euros rescue mechanism for the countries facing financial difficulties. The ECB promised to buy government and private debt to curb the sovereign debt crisis. The meeting agreed to establish the European Financial Stability Facility, the region's temporary bailout mechanism, with initial capital of €440 billion.
The European Financial Stabilisation Mechanism (EFSM) (11/05/2010)	It was established under Regulation (EU) No 407/2010. The regulation gave the European Commission the power to provide financial support to the euro countries. It was a temporary funding mechanism.
European Stability Mechanism (ESM) (11/07/2011, 19/10/2012)	Finance ministers of the 17 euro-area countries signed to establish the European Stability Mechanism (ESM). The European Stability Mechanism (ESM) is a permanent rescue mechanism and replaces the EFSF and the EFSM. It is currently the sole mechanism for providing financial assistance to euro area member states.
Greece bailout (02/05/2010, 21/07/2011)	In 2010, the Euro-region agreed on a 110 billion-euro rescue package for Greece. In 2011, the EU summit passed the second bailout package for Greece and agreed to expand the powers of the EFSF.
Ireland bailout (28/11/2010)	Ireland got 85 billion-euro bailout from the IMF, the European Commission, and the EFSF.
Portugal bailout (16/05/2011)	Portugal's 78 billion-euro bailout was approved by finance ministers of the Eurozone and the IMF.
Spain bailout (09/06/2012)	Spain announced that it needs financial assistance of up to €100 billion. By the end of July, the Eurozone approved to provide financial assistance to Spain.
Cyprus bailout (25/06/2012)	Due to exposure to Greek debt, Cyprus requested a bailout. In March 2013, Cyprus obtained €10 billion bailout from the ESM and the IMF.

Notes: This table briefly presents the details of the major bailouts analysed in this chapter. The news announcement dates and news descriptions are available at the crisis timeline provided by the Federal Reserve Bank of St. Louis, Petrovic and Tutsch (2009), the European crisis timelines provided by Bloomberg, the ESM, and the EFSF.

Appendix 4B: National Equity Index of Each Country

Table 4B: National Equity Index of Each Country

Country	National Equity Index
Austria	Austrian Traded Index (ATX)
Belgium	BEL 20 Index
Cyprus	Stock Exchange General Index
Finland	Nordic Exchange OMX Helsinki (OMXH) Index
France	France CAC 40 Index
Germany	DAX 30 Performance Index
Ireland	Stock Exchange Overall (ISEQ) Index
Italy	Financial Times Stock Exchange MIB Index
Netherlands	Aex Index(AEX)
Portugal	PSI-20 Index
Slovenia	Slovenian Stock Exchange (SBI) Index
Spain	IBEX 35 Index
U.K.	Financial Times Stock Exchange (FTSE) 100 Index
U.S.	S&P 500 Index

Notes: This table reports the name of the national equity index of each examined country used in this study.

Appendix 4C: Full Estimation Results of Table 4.7—Table 4.18

Table 4C.1: Full Results of Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
θ_1	0.028	-0.044***	-0.093***	-0.124***	0.064***
	(0.596)	(0.000)	(0.000)	(0.006)	(0.000)
γ_{11}	0.171***	0.077***	0.130***	0.172***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.294***	-0.360***	-0.345***	-0.130***	-0.219***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
δ_1	-0.940*	-0.043	-0.296	-1.164***	-0.194***
(Rating Events)	(0.070)	(0.931)	(0.647)	(0.000)	(0.000)
c_1	0.034*	-0.031	-0.048**	-0.123***	0.311***
	(0.061)	(0.133)	(0.032)	(0.000)	(0.000)
a_1	0.209***	0.220***	0.281***	0.248***	0.281***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.934***	0.958***	0.947***	0.981***	0.829***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.059***	0.022	0.043***	0.020*	-0.077***
	(0.000)	(0.119)	(0.008)	(0.074)	(0.001)
λ_1	-0.262***	-0.096	0.039	0.188***	-0.352***
(Rating Events)	(0.000)	(0.127)	(0.729)	(0.003)	(0.000)
θ_2	-0.040	-0.050**	-0.044	0.050*	-0.052**
	(0.122)	(0.015)	(0.157)	(0.046)	(0.040)
γ_{21}	-0.020***	-0.019***	-0.017**	0.006	-0.015
	(0.005)	(0.007)	(0.039)	(0.454)	(0.184)
φ_{21}	0.082***	0.002	-0.049*	0.042*	0.100***
	(0.001)	(0.915)	(0.062)	(0.076)	(0.000)
δ_2	0.029	0.090	0.329	0.116	0.024
(Rating Events)	(0.806)	(0.595)	(0.271)	(0.323)	(0.702)
c_2	-0.094***	-0.054***	-0.051***	-0.122***	-0.167***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.156***	0.097***	0.105***	0.167***	0.270***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.946***	0.975***	0.968***	0.985***	0.986***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.134***	-0.139***	-0.122***	-0.054***	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.877)
λ_2	-0.021	-0.039	-0.098	0.045	0.018
(Rating Events)	(0.761)	(0.453)	(0.146)	(0.470)	(0.745)
α	0.167***	0.087***	0.096***	0.139***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
β	0.883***	0.995***	0.994***	0.967***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	-0.158	-0.000	0.000	0.000	-0.383***
	(0.101)	(1.000)	(1.000)	(1.000)	(0.005)
v	0.069**	0.012	0.023***	-0.046	-0.018
(Rating Events)	(0.032)	(0.286)	(0.005)	(0.114)	(0.785)

Table 4C.1: Full Results of Domestic Sovereign Rating Events (Continued)

	Germany	France	Netherlands	Belgium	Austria
θ_1	0.258***	-0.084	0.098***	-0.140***	-0.141***
	(0.000)	(0.261)	(0.000)	(0.000)	(0.020)
γ_{11}	-0.005***	0.080***	0.149***	0.024***	-0.153***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.583***	-0.497***	-0.324***	-0.430***	-0.862***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_1	2.726	0.010	-0.204	0.400	-1.216
(Rating Events)	(0.503)	(0.996)	(0.864)	(0.634)	(0.318)
c_1	0.292***	-0.029	-0.063***	-0.012	-0.001
	(0.000)	(0.106)	(0.000)	(0.556)	(0.902)
a_1	0.261***	0.243***	0.257***	0.294***	0.100***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.861***	0.958***	0.962***	0.940***	0.982***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.047***	0.020	0.082***	-0.020	-0.002
	(0.009)	(0.135)	(0.000)	(0.134)	(0.834)
λ_1	-0.090	0.089	0.271	-0.180	0.528***
(Rating Events)	(0.929)	(0.686)	(0.482)	(0.400)	(0.000)
θ_2	0.008	-0.026	-0.006	-0.013	-0.007
	(0.681)	(0.297)	(0.802)	(0.560)	(0.782)
γ_{21}	-0.002	-0.005	-0.002	-0.008*	0.005
	(0.691)	(0.467)	(0.835)	(0.093)	(0.416)
φ_{21}	0.002	-0.036***	0.024	0.019	0.126***
	(0.941)	(0.001)	(0.304)	(0.367)	(0.000)
δ_2	1.757*	0.166	0.110	0.105	-0.368
(Rating Events)	(0.054)	(0.723)	(0.731)	(0.606)	(0.300)
c_2	-0.074***	-0.057***	-0.075***	-0.086***	-0.087***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.114***	0.095***	0.104***	0.122***	0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.976***	0.972***	0.984***	0.974***	0.973***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.127***	-0.166***	-0.142***	-0.139***	-0.095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_2	-0.149	-0.087	-0.318	0.034	-0.243
(Rating Events)	(0.724)	(0.504)	(0.140)	(0.753)	(0.268)
α	0.106***	0.132***	-0.136*	0.171***	0.143
	(0.000)	(0.000)	(0.097)	(0.000)	(0.120)
β	0.989***	0.988***	-0.000	0.975***	0.643
	(0.000)	(0.000)	(1.000)	(0.000)	(0.122)
g	0.000	-0.000	-0.333**	-0.000	-0.230**
	(1.000)	(1.000)	(0.014)	(1.000)	(0.014)
v	0.203	-0.035	0.740***	0.017	0.441***
(Rating Events)	(0.240)	(0.541)	(0.000)	(0.739)	(0.000)

Table 4C.1: Full Results of Domestic Sovereign Rating Events (Continued)

	Slovenia	Finland	U.S.	U.K.
θ_1	0.090***	-0.018***	-0.075***	-0.074***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_{11}	0.040***	0.020***	-0.037***	-0.151***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_{12}	0.102***			
	(0.000)			
γ_{13}	0.077***			
	(0.000)			
γ_{14}	0.034*			
	(0.056)			
φ_{11}	-0.223***	-0.300***	-0.957***	-0.656***
	(0.000)	(0.000)	(0.000)	(0.000)
φ_{12}	-0.229***			
	(0.000)			
φ_{13}	-0.139***			
	(0.000)			
φ_{14}	-0.110***			
	(0.000)			
δ_1	-0.047*	0.278	-1.542	-0.086
(Rating Events)	(0.085)	(0.555)	(0.351)	(0.845)
c_1	-0.061***	-0.026*	0.016	0.904***
	(0.000)	(0.056)	(0.487)	(0.000)
a_1	0.150***	0.313***	0.318***	0.300***
	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.993***	0.930***	0.929***	0.654***
	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.020*	-0.020	0.066***	-0.019
	(0.068)	(0.166)	(0.000)	(0.513)
λ_1	0.080	0.889**	0.001	3.836***
(Rating Events)	(0.158)	(0.022)	(0.999)	(0.003)
θ_2	0.013	-0.006	0.018	-0.011
	(0.378)	(0.785)	(0.256)	(0.604)
γ_{21}	-0.069***	0.007	-0.013***	-0.001
	(0.000)	(0.420)	(0.001)	(0.525)
γ_{22}	-0.041***			
	(0.000)			
γ_{23}	-0.041***			
	(0.000)			
γ_{24}	-0.025***			
	(0.000)			
φ_{11}	0.008	0.045*	-0.049**	-0.013
	(0.491)	(0.072)	(0.022)	(0.607)
φ_{22}	-0.037			
	(0.104)			
φ_{23}	-0.008			
	(0.746)			
φ_{24}	-0.005			
	(0.823)			
δ_2	-0.072	0.159	0.416	-0.639*
(Rating Events)	(0.518)	(0.668)	(0.110)	(0.056)
c_2	-0.415***	-0.050***	-0.104***	-0.106***
	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.694***	0.073***	0.137***	0.139***
	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.869***	0.989***	0.975***	0.977***
	(0.000)	(0.000)	(0.000)	(0.000)

d_2	0.185***	-0.088***	-0.160***	-0.129***
	(0.000)	(0.000)	(0.000)	(0.000)
λ_2	0.110	0.147	-0.747***	-0.059
(Rating Events)	(0.482)	(0.455)	(0.001)	(0.887)
α	0.192***	-0.000	0.000	0.073***
	(0.000)	(1.000)	(1.000)	(0.000)
β	0.950***	0.346	0.990***	0.998***
	(0.000)	(0.265)	(0.000)	(0.000)
g	-0.000	-0.334**	0.000	0.000
	(1.000)	(0.010)	(1.000)	(1.000)
v	-0.009	-0.685***	0.418***	-0.044
(Rating Events)	(0.863)	(0.000)	(0.000)	(0.345)

Notes: This table reports the full estimation results of Table 4.7. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.2: Full Results of Domestic Positive and Negative Sovereign Rating Events

	Portugal	Spain	Italy	Ireland (GARCH)	Cyprus	Germany
θ_1	0.013	-0.033	-0.051***	-0.134***	0.034***	0.251***
	(0.531)	(0.674)	(0.000)	(0.005)	(0.000)	(0.000)
γ_{11}	0.172***	0.077***	0.143***	0.181***	-0.018***	-0.004***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.296***	-0.359***	-0.346***	-0.122***	-0.180***	-0.590***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
δ_{11} (Positive Rating Events)	0.027**	-0.228	-2.296	-1.835***	-0.016***	1.439
	(0.021)	(0.810)	(0.120)	(0.001)	(0.000)	(0.734)
δ_{12} (Negative Rating Events)	-1.376***	0.017	-0.069	-1.131**	-0.748***	2.952
	(0.000)	(0.976)	(0.888)	(0.011)	(0.003)	(0.466)
c_1	0.033*	-0.032	-0.017	0.076***	0.001	0.318***
	(0.086)	(0.136)	(0.527)	(0.000)	(0.824)	(0.000)
a_1	0.209***	0.219***	0.292***	0.118***	0.105***	0.271***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.935***	0.958***	0.935***	0.888***	0.987***	0.851***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.061***	0.023	0.042***		-0.039***	0.046***
	(0.002)	(0.102)	(0.009)		(0.000)	(0.006)
λ_{11} (Positive Rating Events)	-0.333	-0.031	-0.486	1.323**	-0.857***	-3.384
	(0.222)	(0.870)	(0.248)	(0.040)	(0.000)	(0.205)
λ_{12} (Negative Rating Events)	-0.260***	-0.106	0.074	0.202	0.137***	0.369
	(0.002)	(0.167)	(0.484)	(0.843)	(0.000)	(0.701)
θ_2	-0.038	-0.047**	-0.031	0.076***	-0.053**	0.009
	(0.130)	(0.024)	(0.351)	(0.006)	(0.036)	(0.700)
γ_{21}	-0.020***	-0.019***	-0.017**	0.004	-0.015	-0.002
	(0.003)	(0.007)	(0.044)	(0.613)	(0.217)	(0.693)
φ_{21}	0.083***	0.004	-0.043	0.037	0.100***	0.001
	(0.000)	(0.756)	(0.108)	(0.143)	(0.000)	(0.953)
δ_{21} (Positive Rating Events)	-0.231	-0.194	0.352	-0.067	0.028***	-0.875
	(0.586)	(0.471)	(0.644)	(0.784)	(0.000)	(0.737)
δ_{22} (Negative Rating Events)	0.066	0.267***	0.328	0.139	0.012	2.426**
	(0.612)	(0.000)	(0.317)	(0.122)	(0.897)	(0.047)
c_2	-0.096***	-0.048***	-0.054***	0.026***	-0.168***	-0.074***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
a_2	0.157***	0.092***	0.102***	0.080***	0.270***	0.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	()0.000
b_2	0.946***	0.974***	0.972***	0.909***	0.986***	0.975***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.134***	-0.141***	-0.114***		0.002	-0.127***
	(0.000)	(0.000)	(0.000)		(0.874)	(0.000)
λ_{21} (Positive Rating Events)	0.135	-0.285*	0.002	-0.125	0.034	0.382
	(0.544)	(0.051)	(0.995)	(0.299)	(0.698)	(0.706)
λ_{22} (Negative Rating Events)	-0.041	-0.019	-0.088	0.142***	0.013	-0.264
	(0.567)	(0.693)	(0.203)	(0.000)	(0.834)	(0.546)
α	0.161***	0.080 ***	0.087***	0.125***	-0.000	0.123***
	(0.000)	(0.000)	(0.000)	(0.001)	(1.000)	(0.000)
β	0.895***	0.995***	0.995***	0.968***	0.975***	0.982***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
g	-0.146	0.000	0.000	-0.000	-0.000	0.000
	(0.110)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
v_1 (Positive Rating Events)	0.035	-0.017	-0.032	-0.001	0.097**	-0.198
	(0.808)	(0.348)	(0.537)	(0.987)	(0.018)	(0.691)
v_2 (Negative Rating Events)	0.069**	0.015**	0.021***	-0.083*	-0.040	0.319
	(0.017)	(0.049)	(0.008)	(0.053)	(0.105)	(0.130)

Table 4C.2: Full Results of Domestic Positive and Negative Sovereign Rating Events (Continued)

	France (GJR)	Netherlands	Belgium	Finland	U.S.	U.K.
θ_1	-0.125	0.072	-0.137***	-0.013***	-0.006	-0.072
	(0.136)	(0.163)	(0.000)	(0.000)	(0.291)	(0.459)
γ_{11}	0.076***	0.150***	0.023*	0.032***	0.005***	-0.150***
	(0.005)	(0.000)	(0.067)	(0.000)	(0.002)	(0.000)
φ_{11}	-0.410***	-0.306***	-0.423***	-0.293***	-0.942***	-0.650***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_{11} (Positive		1.912***	0.648	1.510***	-2.373**	5.211
Rating Events)		(0.002)	(0.310)	(0.001)	(0.030)	(0.794)
δ_{12} (Negative	0.262	-2.192***	0.462***	-0.024	2.110	-0.106
Rating Events)	(0.882)	(0.008)	(0.000)	(0.953)	(0.176)	(0.756)
c_1	0.469***	-0.057***	-0.018	-0.021	0.021	0.936***
	(0.000)	(0.000)	(0.341)	(0.119)	(0.500)	(0.000)
a_1	0.117***	0.254***	0.271***	0.299***	0.311***	0.302***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.877***	0.962***	0.948***	0.932***	0.930***	0.644***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	-0.005	0.083***	-0.019	-0.022	0.066***	-0.021
	(0.776)	(0.000)	(0.149)	(0.143)	(0.000)	(0.483)
λ_{11} (Positive		-0.779**	-1.454***	-2.666***	-0.827*	2.923*
Rating Events)		(0.042)	(0.000)	(0.001)	(0.085)	(0.083)
λ_{12} (Negative	5.072	1.340***	0.218	1.572***	0.672**	4.382***
Rating Events)	(0.329)	(0.000)	(0.282)	(0.000)	(0.043)	(0.001)
θ_2	-0.016	-0.003	-0.008	-0.005	0.018	-0.002
	(0.552)	(0.905)	(0.308)	(0.808)	(0.301)	(0.880)
γ_{21}	-0.005	-0.002	-0.008*	0.007	-0.014***	0.000
	(0.431)	(0.785)	(0.099)	(0.415)	(0.004)	(0.906)
φ_{21}	-0.041*	0.020	0.024	0.045***	-0.049**	-0.014
	(0.097)	(0.364)	(0.233)	(0.000)	(0.021)	(0.540)
δ_{21} (Positive		-0.426	-0.096	-0.281	0.371	-0.911***
Rating Events)		(0.298)	(0.814)	(0.731)	(0.261)	(0.002)
δ_{22} (Negative	0.214	0.757	0.533	0.358	1.273	-0.191
Rating Events)	(0.634)	(0.160)	(0.127)	(0.402)	(0.291)	(0.507)
c_2	0.039***	-0.074***	-0.091***	-0.050***	-0.103***	-0.115***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	-0.029***	0.103***	0.125***	0.073***	0.136***	0.151***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.913***	0.984***	0.975***	0.989***	0.975***	0.970***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	0.201***	-0.142***	-0.144***	-0.088***	-0.161***	-0.137***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{21} (Positive		-0.568*	0.657**	0.001	-0.817**	-1.093
Rating Events)		(0.066)	(0.012)	(0.998)	(0.048)	(0.152)
λ_{22} (Negative	-0.189	-0.091	-0.143	0.193	-0.762***	0.685
Rating Events)	(0.513)	(0.755)	(0.312)	(0.422)	(0.004)	(0.205)
α	0.137***	-0.168**	0.170***	-0.000	-0.000	0.051*
	(0.000)	(0.014)	(0.000)	(1.000)	(1.000)	(0.088)
β	0.987***	-0.000	0.975***	0.329	0.995***	0.999***
	(0.000)	(1.000)	(0.000)	(0.283)	(0.000)	(0.000)
g	-0.000	-0.411***	-0.000	-0.340***	0.000	-0.000
	(1.000)	(0.000)	(1.000)	(0.003)	(1.000)	(1.000)
v_1 (Positive		0.715	-0.090	-0.692***	0.030	0.112
Rating Events)		(0.187)	(0.286)	(0.000)	(0.650)	(0.524)

v_2 (Negative Rating Events)	-0.025 (0.672)	0.593*** (0.000)	0.044 (0.424)	-0.686 (0.170)	0.375*** (0.000)	-0.128 (0.179)

Notes: This table reports the full estimation results of Table 4.8.

GARCH:

$$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + \lambda_{11} Positive\ Rating\ Events_t + \lambda_{12} Negative\ Rating\ Events_t$$
$$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + \lambda_{21} Positive\ Rating\ Events_t + \lambda_{22} Negative\ Rating\ Events_t$$

GJR:

$$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_{11} Positive\ Rating\ Events_t + \lambda_{12} Negative\ Rating\ Events_t$$
$$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_{21} Positive\ Rating\ Events_t + \lambda_{22} Negative\ Rating\ Events_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.3: Full Results of Domestic Sovereign Rating Surprises

	Austria	Cyprus (E)	France	Ireland	Italy (E)	Spain
θ_1	-0.133***	0.043**	-0.082	-0.137	-0.124***	-0.046
	(0.000)	(0.022)	(0.299)	(0.568)	(0.000)	(0.580)
γ_{11}	-0.153***	-0.007**	0.081***	0.177***	0.124***	0.076***
	(0.000)	(0.013)	(0.002)	(0.000)	(0.000)	(0.004)
φ_{11}	-0.882***	-0.216***	-0.495***	-0.122	-0.353***	-0.360***
	(0.000)	(0.000)	(0.000)	(0.574)	(0.000)	(0.000)
δ_1 (Rating	-2.162	-0.019***	-0.888	-2.314*	-1.604	0.497
Surprises)	(0.379)	(0.001)	(0.904)	(0.058)	(0.734)	(0.728)
c_1	-0.002	0.023***	-0.029	-0.126***	-0.055**	-0.031
	(0.884)	(0.000)	(0.101)	(0.000)	(0.013)	(0.204)
a_1	0.108***	0.108***	0.243***	0.255***	0.289***	0.223***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.980***	0.974***	0.958***	0.980***	0.948***	0.957***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	-0.007		0.020	0.018		0.021
	(0.526)		(0.124)	(0.470)		(0.161)
λ_1 (Rating	-0.035	-1.388***	0.400	0.567*	0.084	-0.173
Surprises)	(0.932)	(0.000)	(0.560)	(0.055)	(0.915)	(0.609)
θ_2	-0.005	-0.041*	-0.026***	0.050**	0.014	-0.049**
	(0.842)	(0.068)	(0.000)	(0.032)	(0.652)	(0.039)
γ_{21}	0.005	-0.012	-0.005***	0.006	-0.019**	-0.019***
	(0.417)	(0.281)	(0.000)	(0.414)	(0.027)	(0.000)
φ_{21}	0.124***	0.104***	-0.036***	0.042*	-0.068***	0.004
	(0.000)	(0.000)	(0.000)	(0.083)	(0.004)	(0.844)
δ_2 (Rating	-0.600	-0.042	-0.571	0.076	-1.719	-0.292
Surprises)	(0.380)	(0.480)	(0.684)	(0.844)	(0.575)	(0.657)
c_2	-0.087***	-0.168***	-0.056***	-0.122***	-0.107***	-0.049***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.120***	0.270***	0.094***	0.167***	0.174***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.975***	0.986***	0.973***	0.984***	0.975***	0.974***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.086***		-0.165***	-0.056***		-0.139***
	(0.000)		(0.000)	(0.000)		(0.000)
λ_2 (Rating	0.312	0.229	-0.395	0.197	-0.170	-0.295
Surprises)	(0.600)	(0.212)	(0.414)	(0.401)	(0.802)	(0.180)
α	0.162*	-0.000	0.137***	0.150***	0.098***	0.090***
	(0.063)	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	-0.451	0.810***	0.986***	0.961***	0.995***	0.996***
	(0.281)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
g	-0.221**	-0.227	-0.000	-0.000	-0.000	0.000
	(0.046)	(0.151)	(1.000)	(1.000)	(1.000)	(1.000)
v (Rating	0.809***	0.262***	0.040	-0.070	0.204***	-0.050
Surprises)	(0.000)	(0.000)	(0.857)	(0.593)	(0.006)	(0.144)

Notes: This table reports the full estimation results of Table 4.9.

EGARCH without asymmetry (E):

$$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_1 Rating\ Surprises_t$$

$$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_2 Rating\ Surprises_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.4: Full Results of Bailout Events

	Portugal (GJR)	Spain	Italy	Ireland (GJR)	Cyprus (GJR)
θ_1	0.035	-0.045***	-0.095**	-0.132**	0.064
	(0.655)	(0.000)	(0.029)	(0.010)	(0.363)
γ_{11}	0.188***	0.077***	0.134***	0.183***	0.030
	(0.000)	(0.000)	(0.000)	(0.000)	(0.347)
φ_{11}	-0.249***	-0.360***	-0.350***	-0.120***	-0.137***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
δ_1	-4.781***	1.253***	1.997***	-1.339	3.412***
(Bailout Events)	(0.000)	(0.000)	(0.000)	(0.344)	(0.001)
c_1	0.790***	-0.010	-0.024	0.093***	2.767***
	(0.000)	(0.709)	(0.289)	(0.000)	(0.000)
a_1	0.159***	0.224***	0.275***	0.132***	0.077***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.838***	0.949***	0.938***	0.886***	0.688***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	-0.071***	0.015	0.032*	-0.026	0.152***
	(0.004)	(0.364)	(0.067)	(0.199)	(0.000)
λ_1	-0.985	0.591***	0.862***	2.229	7.329
(Bailout Events)	(0.846)	(0.009)	(0.000)	(0.407)	(0.205)
θ_2	-0.034	-0.047*	-0.040**	0.049*	-0.050**
	(0.194)	(0.083)	(0.014)	(0.091)	(0.046)
γ_{21}	-0.025***	-0.019***	-0.017***	0.003	-0.018
	(0.001)	(0.009)	(0.000)	(0.677)	(0.168)
φ_{21}	0.079***	0.005	-0.050**	0.043*	0.117***
	(0.002)	(0.844)	(0.026)	(0.080)	(0.000)
δ_2	-0.966**	-1.092	-1.297**	-0.423	-0.865
(Bailout Events)	(0.044)	(0.101)	(0.043)	(0.243)	(0.394)
c_2	0.105***	-0.051***	-0.054***	0.031***	0.008***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.007)
a_2	0.005	0.091***	0.106***	0.040***	0.136***
	(0.741)	(0.000)	(0.000)	(0.004)	(0.000)
b_2	0.839***	0.975***	0.969***	0.906***	0.885***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	0.198***	-0.134***	-0.116***	0.075***	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.942)
λ_2	0.432	0.380***	0.355**	-0.079	4.605*
(Bailout Events)	(0.437)	(0.003)	(0.020)	(0.693)	(0.067)
α	0.169***	-0.074***	0.103***	0.133*	0.040
	(0.000)	(0.000)	(0.000)	(0.065)	(0.944)
β	0.881***	0.997***	0.994***	0.808***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	0.137*	0.000	0.000	0.284***	-0.389**
	(0.072)	(1.000)	(1.000)	(0.000)	(0.007)
v	-0.288***	-0.035*	-0.032	-0.563***	-0.204
(Bailout Events)	(0.003)	(0.062)	(0.175)	(0.000)	(0.219)

Table 4C.4: Full Results of Bailout Events (Continued)

	Germany	France	Netherlands	Belgium (GJR)	Austria (GJR)
θ_1	0.255**	-0.082	0.084	-0.091	-0.178*
	(0.011)	(0.300)	(0.111)	(0.230)	(0.059)
γ_{11}	0.002	0.082***	0.145***	0.059**	-0.107***
	(0.936)	(0.001)	(0.000)	(0.028)	(0.000)
φ_{11}	-0.582***	-0.501***	-0.327***	-0.333***	-0.513***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_1	2.000	0.603	0.456	-0.571	1.546
(Bailout Events)	(0.413)	(0.763)	(0.721)	(0.767)	(0.393)
c_1	0.326***	-0.022	-0.062***	0.409***	0.247***
	(0.000)	(0.238)	(0.000)	(0.001)	(0.000)
a_1	0.261***	0.242***	0.259***	0.078***	0.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.849***	0.955***	0.961***	0.889***	0.940***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.051***	0.020	0.082***	0.040**	0.039***
	(0.006)	(0.148)	(0.000)	(0.027)	(0.001)
λ_1	0.550*	0.331*	0.009	13.923*	11.255**
(Bailout Events)	(0.071)	(0.078)	(0.961)	(0.053)	(0.011)
θ_2	0.011	-0.023	-0.001	-0.001	-0.002
	(0.460)	(0.317)	(0.955)	(0.972)	(0.945)
γ_{21}	-0.003	-0.005	-0.002	-0.006	0.003
	(0.617)	(0.373)	(0.762)	(0.253)	(0.635)
φ_{21}	0.001	-0.036	0.022	0.026	0.122***
	(0.949)	(0.115)	(0.376)	(0.283)	(0.000)
δ_2	-0.779***	-0.839*	-0.606	-0.605	-0.329
(Bailout Events)	(0.000)	(0.075)	(0.115)	(0.191)	(0.426)
c_2	-0.075***	-0.057***	-0.076***	0.030***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
a_2	0.114***	0.095***	0.105***	-0.010	0.005
	(0.000)	(0.000)	(0.000)	(0.262)	(0.578)
b_2	0.976***	0.972***	0.985***	0.908***	0.926***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.127***	-0.164***	-0.138***	0.168***	0.096***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_2	0.158	0.144	0.126	0.414*	0.529*
(Bailout Events)	(0.239)	(0.242)	(0.320)	(0.092)	(0.049)
α	0.036	0.124***	-0.144*	0.143***	0.167**
	(0.177)	(0.000)	(0.062)	(0.000)	(0.012)
β	0.997***	0.988***	-0.000	0.975***	-0.452
	(0.000)	(0.000)	(1.000)	(0.000)	(0.340)
g	-0.000	-0.000	-0.360***	-0.000	-0.188*
	(1.000)	(1.000)	(0.003)	(1.000)	(0.091)
v	-0.087***	-0.112***	-0.119	-0.179***	-0.049
(Bailout Events)	(0.000)	(0.007)	(0.622)	(0.000)	(0.801)

Table 4C.4: Full Results of Bailout Events (Continued)

	Slovenia (GJR)	Finland (GJR)	U.S. (GARCH)	U.K.
θ_1	-0.027	-0.034	-0.145**	-0.102
	(0.564)	(0.505)	(0.016)	(0.227)
γ_{11}	0.022	0.063**	0.018	-0.090***
	(0.422)	(0.041)	(0.580)	(0.000)
γ_{12}	0.093***			
	(0.000)			
γ_{13}	0.072***			
	(0.006)			
γ_{14}	0.003			
	(0.912)			
φ_{11}	-0.107***	-0.244***	-0.338***	-0.559***
	(0.005)	(0.000)	(0.000)	(0.000)
φ_{12}	-0.090**			
	(0.023)			
φ_{13}	-0.033			
	(0.397)			
φ_{14}	-0.046			
	(0.250)			
δ_1	-0.553	-0.214	0.043	-0.611
(Bailout Events)	(0.655)	(0.855)	(0.993)	(0.431)
c_1	0.017***	0.387***	0.724***	3.985***
	(0.000)	(0.000)	(0.001)	(0.000)
a_1	0.046***	0.123***	0.122***	0.420***
	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.955***	0.829***	0.836***	-0.363***
	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.001	0.063**		-0.107***
	(0.917)	(0.011)		(0.000)
λ_1	6.650***	7.941**	14.671***	-3.079***
(Bailout Events)	(0.001)	(0.032)	(0.000)	(0.000)
θ_2	-0.019	0.009	0.063***	-0.004
	(0.434)	(0.703)	(0.001)	(0.820)
γ_{21}	-0.067***	0.004	-0.015***	-0.001
	(0.000)	(0.608)	(0.002)	(0.866)
γ_{22}	-0.048***			
	(0.000)			
γ_{23}	-0.041***			
	(0.000)			
γ_{24}	-0.027***			
	(0.000)			
φ_{11}	-0.009	0.032	-0.062***	-0.015
	(0.777)	(0.172)	(0.009)	(0.538)
φ_{22}	-0.054*			
	(0.040)			
φ_{23}	-0.018			
	(0.437)			
φ_{24}	-0.003			
	(0.885)			
δ_2	0.271	-0.913**	0.476	-0.631
(Bailout Events)	(0.425)	(0.033)	(0.499)	(0.715)
c_2	0.210***	0.017***	0.023***	-0.109***
	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.919***	0.000	0.113***	0.141***
	(0.000)	(0.972)	(0.000)	(0.000)
b_2	0.462***	0.943***	0.869***	0.975***
	(0.000)	(0.000)	(0.000)	(0.000)

d_2	-0.480***	0.095***		-0.129***
	(0.000)	(0.000)		(0.000)
λ_2	0.398	-0.001	1.237	0.412
(Bailout Events)	(0.407)	(0.997)	(0.220)	(0.372)
α	0.260***	0.071***	-0.000	0.051***
	(0.000)	(0.003)	(1.000)	(0.000)
β	0.430**	0.994***	0.996***	0.999***
	(0.029)	(0.000)	(0.000)	(0.000)
g	-0.000	-0.062	0.000	0.000
	(1.000)	(0.142)	(1.000)	(1.000)
v	-0.362*	-0.092**	-0.305***	-0.099***
(Bailout Events)	(0.062)	(0.014)	(0.000)	(0.006)

Notes: This table reports the full estimation results of Table 4.10.

GJR:

$$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_1 Bailout\ Events_t$$
$$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_2 Bailout\ Events_t$$

GARCH:
$$log\ h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1 h_{1t-1} + \lambda_1 Bailout\ Events_t$$
$$log\ h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2 h_{2t-1} + \lambda_2 Bailout\ Events_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.5: Full Results of Bailouts and Domestic Sovereign Rating Events

	Portugal (E)	Spain	Italy (GJR)	Ireland	Cyprus (E)
θ_1	0.044***	-0.046***	-0.047	-0.123***	0.104***
	(0.000)	(0.000)	(0.552)	(0.000)	(0.000)
γ_{11}	0.178***	0.078***	0.138***	0.171***	0.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.271***	-0.361***	-0.341***	-0.130***	-0.188***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_{11}	-0.925*	0.045	-0.377	-1.166***	-0.364*
(Rating Events)	(0.088)	(0.934)	(0.567)	(0.000)	(0.077)
δ_{12}	-4.849*	1.250***	0.127	-1.708	1.853
(Bailout Events)	(0.075)	(0.000)	(0.956)	(0.180)	(0.247)
c_1	0.104***	-0.007	0.918***	-0.120***	0.408***
	(0.004)	(0.818)	(0.000)	(0.000)	(0.000)
a_1	0.272***	0.225***	0.191***	0.251***	0.290***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.890***	0.947***	0.796***	0.978***	0.789***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1		0.015	-0.048	0.020**	
		(0.337)	(0.108)	(0.023)	
λ_{11}	-0.314***	-0.077	-0.061	0.196***	-0.393***
(Rating Events)	(0.000)	(0.386)	(0.976)	(0.000)	(0.000)
λ_{12}	1.217***	0.577**	33.850**	0.315*	0.351
(Bailout Events)	(0.000)	(0.011)	(0.029)	(0.071)	(0.301)
θ_2	0.032	-0.046	-0.037	0.053**	-0.053***
	(0.239)	(0.120)	(0.251)	(0.042)	(0.000)
γ_{21}	-0.023***	-0.019**	-0.020**	0.005	-0.012***
	(0.001)	(0.014)	(0.014)	(0.495)	(0.000)
φ_{21}	0.062**	0.004	-0.058**	0.041**	0.101***
	(0.018)	(0.857)	(0.026)	(0.041)	(0.000)
δ_{21}	0.038	0.088	0.110	0.114	0.021
(Rating Events)	(0.749)	(0.588)	(0.691)	(0.305)	(0.702)
δ_{22}	-0.800	-1.097*	-0.991*	-0.518***	-1.130
(Bailout Events)	(0.135)	(0.074)	(0.091)	(0.000)	(0.213)
c_2	-0.159***	-0.051***	0.081***	-0.122***	-0.167***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.234***	0.090***	-0.021**	0.168***	0.270***
	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)
b_2	0.957***	0.975***	0.909***	0.984***	0.985***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2		-0.134***	0.160***	-0.055***	
		(0.000)	(0.000)	(0.000)	
λ_{21}	-0.033	-0.002	-0.202	0.043	0.045
(Rating Events)	(0.616)	(0.971)	(0.438)	(0.491)	(0.334)
λ_{22}	0.438**	0.382***	1.407**	0.012	0.449***
(Bailout Events)	(0.015)	(0.005)	(0.040)	(0.945)	(0.005)
α	0.198***	-0.079***	0.080***	0.131***	-0.000
	(0.000)	(0.000)	(0.000)	(0.005)	(1.000)
β	0.827***	0.996***	0.996***	0.954***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	0.211***	0.000	0.000	0.103	-0.355**
	(0.000)	(0.983)	(1.000)	(0.449)	(0.013)
v_1	0.045	0.005***	0.019**	-0.050	-0.022
(Rating Events)	(0.274)	(0.000)	(0.015)	(0.246)	(0.726)
v_2	-0.458***	-0.024	-0.020	-0.330**	-0.137
(Bailout Events)	(0.000)	(0.180)	(0.342)	(0.023)	(0.414)

Table 4C.5: Full Results of Bailouts and Domestic Sovereign Rating Events

(Continued)

	Germany	France	Netherlands (GARCH)	Belgium	Austria
θ_1	0.275***	-0.084***	-0.059	-0.140***	-0.147***
	(0.000)	(0.000)	(0.296)	(0.000)	(0.000)
γ_{11}	0.000	0.081***	0.120***	0.024***	-0.150***
	(0.758)	(0.002)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.569***	-0.502***	-0.321***	-0.432***	-0.835***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_{11}	2.705	0.015	0.061	0.447***	-1.210
(Rating Events)	(0.573)	(0.994)	(0.966)	(0.000)	(0.307)
δ_{12}	-0.674	0.603	0.588	-0.672***	0.522
(Bailout Events)	(0.801)	(0.772)	(0.579)	(0.000)	(0.772)
c_1	0.329***	-0.023	0.236***	0.004	0.005
	(0.000)	(0.220)	0.000)	(0.877)	(0.633)
a_1	0.262***	0.242***	0.140***	0.301***	0.095***
	(0.000)	(0.000)	0.000)	(0.000)	(0.000)
b_1	0.848***	0.955***	0.868***	0.932***	0.980***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.051***	0.020		-0.026*	-0.007
	(0.009)	(0.169)		(0.081)	(0.546)
λ_{11}	-0.131	0.056	0.568	-0.208	0.477***
(Rating Events)	(0.895)	(0.809)	(0.867)	(0.213)	(0.006)
λ_{12}	0.565*	0.327	-0.749	0.488**	0.369***
(Bailout Events)	(0.063)	(0.102)	(0.771)	(0.030)	(0.004)
θ_2	0.012**	-0.023	0.053**	-0.009	0.003
	(0.029)	(0.361)	(0.029)	(0.669)	(0.910)
γ_{21}	-0.002	-0.004	-0.005	-0.008	0.005
	(0.730)	(0.444)	(0.582)	(0.100)	(0.413)
φ_{21}	0.001	-0.036*	0.010	0.020	0.124***
	(0.957)	(0.096)	(0.673)	(0.375)	(0.000)
δ_{21}	1.760*	0.171	0.144	0.091	-0.369
(Rating Events)	(0.057)	(0.706)	(0.722)	(0.669)	(0.318)
δ_{22}	-0.778***	-0.839*	-0.441	-0.496	-0.421
(Bailout Events)	(0.000)	(0.050)	(0.306)	(0.232)	(0.360)
c_2	-0.075***	-0.057***	0.021***	-0.086***	-0.084***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
a_2	0.114***	0.095***	0.092***	0.121***	0.112***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.976***	0.972***	0.897***	0.974***	0.975***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.127***	-0.164***		-0.135***	-0.086***
	(0.000)	(0.000)		(0.000)	(0.000)
λ_{21}	-0.142	-0.090	-0.219	0.038	-0.238
(Rating Events)	(0.707)	(0.505)	(0.445)	(0.720)	(0.260)
λ_{22}	0.147	0.148	0.585*	0.200	0.347**
(Bailout Events)	(0.250)	(0.262)	(0.057)	(0.152)	(0.014)
α	0.026	0.124***	-0.154**	0.160***	0.000
	(0.416)	(0.000)	(0.025)	(0.000)	(1.000)
β	0.998***	0.988***	-0.000	0.964***	-0.997***
	(0.000)	(0.000)	(1.000)	(0.000)	(0.000)
g	-0.000	-0.000	-0.462***	0.107	0.000
	(1.000)	(1.000)	(0.000)	(0.153)	(1.000)
v_1	-0.104	-0.007	0.654***	0.068	0.223***
(Rating Events)	(0.335)	(0.905)	(0.000)	(0.303)	(0.000)
v_2	-0.090***	-0.109**	-0.084	-0.252***	-0.070***
(Bailout Events)	(0.000)	(0.014)	(0.703)	(0.000)	(0.000)

Table 4C.5: Full Results of Bailouts and Domestic Sovereign Rating Events

(Continued)

	Slovenia	Finland (E)	U.S.	U.K. (E)
θ_1	0.091***	-0.102***	-0.148***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_{11}	0.042***	0.030	-0.038	-0.153***
	(0.006)	(0.273)	(0.283)	(0.000)
γ_{12}	0.105***			
	(0.000)			
γ_{13}	0.081***			
	(0.000)			
γ_{14}	0.032***			
	(0.006)			
φ_{11}	-0.212***	-0.281***	-0.495***	-0.657***
	(0.000)	(0.000)	(0.000)	(0.000)
φ_{12}	-0.228***			
	(0.000)			
φ_{13}	-0.144***			
	(0.000)			
φ_{14}	-0.116***			
	(0.000)			
δ_{11}	0.162	0.218	-0.971	-0.070
(Rating Events)	(0.530)	(0.684)	(0.574)	(0.848)
δ_{12}	-0.967	-0.278	-4.298	-1.705***
(Bailout Events)	(0.146)	()0.788	(0.560)	(0.000)
c_1	-0.060***	-0.024	0.060***	0.882***
	(0.000)	(0.122)	(0.000)	(0.000)
a_1	0.147***	0.325***	0.265***	0.301***
	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.993***	0.925***	0.916***	0.661***
	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.018*		0.095***	
	(0.051)		(0.000)	
λ_{11}	0.086**	0.894**	0.310	3.765***
(Rating Events)	(0.043)	(0.017)	(0.427)	(0.000)
λ_{12}	0.219**	0.468**	3.065***	0.425
(Bailout Events)	(0.018)	(0.040)	(0.000)	(0.662)
θ_2	0.012	0.038	0.019	0.051***
	(0.516)	(0.117)	(0.293)	(0.009)
γ_{21}	-0.069***	0.009	-0.013***	-0.002
	(0.000)	(0.321)	(0.006)	(0.646)
γ_{22}	-0.041***			
	(0.000)			
γ_{23}	-0.041***			
	(0.000)			
γ_{24}	-0.025***			
	(0.000)			
φ_{11}	0.008	0.033	-0.048**	-0.018
	(0.758)	(0.154)	(0.026)	(0.445)
φ_{22}	-0.039*			
	(0.099)			
φ_{23}	-0.004			
	(0.853)			
φ_{24}	-0.003			
	(0.882)			
δ_{21}	-0.072	0.298	0.423	-0.566
(Rating Events)	(0.456)	(0.483)	(0.188)	(0.132)

δ_{22}	0.127	-0.956**	0.593	-1.344
(Bailout Events)	(0.671)	(0.027)	(0.422)	(0.455)
c_2	-0.416***	-0.095***	-0.086***	-0.168***
	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.695***	0.132***	0.109***	0.222***
	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.869***	0.989***	0.976***	0.974***
	(0.000)	(0.000)	(0.000)	(0.000)
d_2	0.185***		-0.150***	
	(0.000)		(0.000)	
λ_{21}	0.109	0.059	-0.754***	0.117
(Rating Events)	(0.486)	(0.817)	(0.001)	(0.816)
λ_{22}	-0.037	0.241*	0.674***	0.879*
(Bailout Events)	(0.897)	(0.052)	(0.001)	(0.077)
α	0.134***	-0.039	0.000	0.255***
	(0.001)	(0.243)	(1.000)	(0.000)
β	0.974***	0.997***	0.994***	0.801***
	(0.000)	(0.000)	(0.000)	(0.000)
g	-0.000	-0.000	-0.044***	0.000
	(1.000)	(1.000)	(0.000)	(1.000)
v_1	-0.023	0.120**	0.032	0.190
(Rating Events)	(0.578)	(0.020)	(0.725)	(0.742)
v_2	-0.257***	-0.108***	-0.371***	-0.809***
(Bailout Events)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: This table reports the full estimation results of Table 4.11.

GARCH:
$$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + \lambda_{11}RatingEvents_t + \lambda_{12}BailoutEvents_t$$
$$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + \lambda_{21}RatingEvents_t + \lambda_{22}BailoutEvents_t$$

GJR:
$$h_{1t} = c_1 + a_1\varepsilon_{1t-1}^2 + b_1h_{1t-1} + d_1\varepsilon_{1t-1}^2 I_{\varepsilon<0}(\varepsilon_{1t-1}) + \lambda_{11}RatingEvents_t + \lambda_{12}BailoutEvents_t$$
$$h_{2t} = c_2 + a_2\varepsilon_{2t-1}^2 + b_2h_{2t-1} + d_2\varepsilon_{2t-1}^2 I_{\varepsilon<0}(\varepsilon_{2t-1}) + \lambda_{21}RatingEvents_t + \lambda_{22}BailoutEvents_t$$

EGARCH without asymmetry (E):
$$log\ h_{1t} = c_1 + a_1\frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_{11}RatingEvents_t + \lambda_{12}BailoutEvents_t$$
$$log\ h_{2t} = c_2 + a_2\frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_{21}RatingEvents_t + \lambda_{22}BailoutEvents_t$$

The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.6: Full Results of Spillover Effect of Greek Sovereign Rating Events

	Portugal	Spain	Italy	Ireland (ET)	Cyprus
θ_1	0.056	-0.048**	-0.084***	-0.051**	0.092***
	(0.247)	(0.045)	(0.000)	(0.011)	(0.000)
γ_{11}	0.176***	0.084***	0.136***	0.107***	0.072***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
φ_{11}	-0.277***	-0.360***	-0.351***	-0.067***	-0.198***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_{11} (Domestic	-0.854*	0.095***	-0.421	-0.703***	-0.503*
Rating Events)	(0.071)	(0.003)	(0.497)	(0.000)	(0.057)
δ_{12} (Greek Rating	-0.262***	-0.123	-0.083	-0.260***	-0.050***
Events)	(0.000)	(0.592)	(0.734)	(0.001)	(0.000)
δ_{13} (Bailout	-4.332***	0.466	1.981***	-1.360	1.441***
Events)	(0.000)	(0.846)	(0.000)	(0.162)	(0.000)
c_1	0.097***	0.021	-0.009	0.031	0.480**
	(0.004)	(0.527)	(0.719)	(0.662)	(0.012)
a_1	0.248***	0.226***	0.273***	13.025***	0.330***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.898***	0.936***	0.932***	0.968***	0.750***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1	0.045**	0.011	0.033**		-0.075**
	(0.010)	(0.531)	(0.047)		(0.023)
λ_{11} (Domestic	-0.306***	-0.059	0.019	0.151	-0.311***
Rating Events)	(0.000)	(0.504)	(0.863)	(0.262)	(0.000)
λ_{12} (Greek Rating	-0.024	-0.221***	-0.184***	-0.236***	-0.327**
Events)	(0.700)	(0.000)	(0.001)	(0.001)	(0.016)
λ_{13} (Bailout	1.080***	0.533**	0.818***	0.686**	0.373
Events)	(0.000)	(0.038)	(0.001)	(0.030)	(0.302)
Shape				2.000***	
				(0.000)	
θ_2	-0.035*	-0.044	-0.036	0.086***	-0.053***
	(0.089)	(0.134)	(0.260)	(0.001)	(0.000)
γ_{21}	-0.022***	-0.019***	-0.016*	0.007	-0.012***
	(0.002)	(0.007)	(0.089)	(0.388)	(0.000)
φ_{21}	0.088***	0.005	-0.049*	0.032	0.100***
	(0.000)	(0.755)	(0.059)	(0.163)	(0.000)
δ_{21} (Domestic	0.024	0.068	0.307	0.064	0.020
Rating Events)	(0.802)	(0.642)	(0.299)	(0.524)	(0.743)
δ_{22} (Greek Rating	0.088	0.213**	0.200**	0.078	0.032
Events)	(0.301)	(0.017)	(0.029)	(0.234)	(0.794)
δ_{23} (Bailout	-1.057*	-1.112*	-1.287*	-0.555	-1.093
Events)	(0.059)	(0.072)	(0.055)	(0.110)	(0.238)
c_2	-0.090***	-0.053***	-0.052***	-0.117***	-0.168***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.150***	0.093***	0.103***	0.159***	0.271***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.943***	0.975***	0.968***	0.988***	0.985***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2	-0.137***	-0.135***	-0.119***		0.002
	(0.000)	(0.000)	(0.000)		(0.883)
λ_{21} (Domestic	0.013	-0.001	-0.100	0.098	0.044
Rating Events)	(0.841)	(0.982)	(0.147)	(0.129)	(0.417)
λ_{22} (Greek Rating	-0.056	-0.023	0.003	-0.070*	0.024
Events)	(0.267)	(0.435)	(0.924)	(0.079)	(0.608)
λ_{23} (Bailout	0.346*	0.367***	0.378**	0.055	0.471**
Events)	(0.093)	(0.008)	(0.013)	(0.758)	(0.014)
Shape				8.689***	
				(0.000)	

α	0.158***	0.071***	0.079***	0.183	-0.000
	(0.000)	(0.000)	(0.000)	(0.108)	(1.000)
β	0.849***	0.998***	0.997***	0.837***	-0.804***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
g	-0.211***	0.000	-0.000	-0.352***	-0.164
	(0.000)	(1.000)	(1.000)	(0.007)	(0.624)
v_1 (Domestic Rating Events)	0.065**	0.002	0.011	-0.005***	-0.082
	(0.031)	(0.784)	(0.257)	(0.000)	(0.173)
v_2 (Greek Rating Events)	0.045*	0.007	0.007	0.001	0.022
	(0.063)	(0.121)	(0.277)	(0.544)	(0.686)
v_3 (Bailout Events)	-0.403***	0.005	-0.002	-0.001	-0.093
	(0.000)	(0.872)	(0.957)	(0.932)	(0.598)

Table 4C.6: Full Results of Spillover Effect of Greek Sovereign Rating Events

(Continued)

	Germany (E)	France	Netherlands	Belgium	Austria
θ_1	0.185***	-0.085***	0.087***	-0.127***	-0.126***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
γ_{11}	0.001	0.079***	0.144***	0.033***	-0.141***
	(0.972)	(0.000)	(0.000)	(0.001)	(0.000)
φ_{11}	-0.597***	-0.504***	-0.333***	-0.420***	-0.735***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_{11} (Domestic Rating Events)	2.399	-0.049	-0.229	0.459***	-1.150
	(0.559)	(0.980)	(0.796)	(0.000)	(0.362)
δ_{12} (Greek Rating Events)	-0.184	-0.209	-0.002	-0.058	-0.044
	(0.497)	(0.329)	(0.905)	(0.816)	(0.841)
δ_{13} (Bailout Events)	2.203	0.607	0.425	-0.692***	0.884
	(0.349)	(0.750)	(0.735)	(0.000)	(0.649)
c_1	0.307***	-0.024	-0.064***	0.024	0.004
	(0.000)	(0.181)	(0.000)	(0.379)	(0.620)
a_1	0.270***	0.241***	0.257***	0.299***	0.083***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_1	0.852***	0.956***	0.963***	0.924***	0.982***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_1		0.020*	0.081***	-0.029*	-0.002
		(0.090)	(0.000)	(0.071)	(0.805)
λ_{11} (Domestic Rating Events)	-0.192	0.055	0.271	-0.179	0.491***
	(0.854)	(0.804)	(0.432)	(0.421)	(0.001)
λ_{12} (Greek Rating Events)	-0.233***	-0.022	-0.034	-0.205***	-0.126***
	(0.000)	(0.653)	(0.454)	(0.000)	(0.000)
λ_{13} (Bailout Events)	0.463*	0.297	-0.022	0.458**	0.195*
	(0.098)	(0.113)	(0.898)	(0.029)	(0.072)
θ_2	0.073***	-0.021	-0.002	-0.007	0.005
	(0.004)	(0.369)	(0.920)	(0.717)	(0.836)
γ_{21}	-0.002	-0.004	-0.002	-0.009*	0.005
	(0.740)	(0.499)	(0.815)	(0.082)	(0.413)
φ_{21}	-0.012	-0.036	0.024	0.018	0.123***
	(0.639)	(0.124)	(0.317)	(0.430)	(0.000)
δ_{21} (Domestic Rating Events)	1.852	0.192	0.116	0.091	-0.369
	(0.136)	(0.685)	(0.723)	(0.664)	(0.289)
δ_{22} (Greek Rating Events)	0.129*	0.141**	0.105*	0.116*	0.075
	(0.057)	(0.048)	(0.089)	(0.061)	(0.254)
δ_{23} (Bailout Events)	-0.676	-0.842*	-0.621*	-0.499	-0.424
	(0.137)	(0.074)	(0.098)	(0.193)	(0.316)
c_2	-0.124***	-0.057***	-0.077***	-0.086***	-0.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2	0.176***	0.094***	0.106***	0.120***	0.111***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_2	0.983***	0.973***	0.984***	0.975***	0.975***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d_2		-0.163***	-0.142***	-0.134***	-0.086***
		(0.000)	(0.000)	(0.000)	(0.000)
λ_{21} (Domestic Rating Events)	0.012	-0.102	-0.307	0.044	-0.235
	(0.980)	(0.409)	(0.180)	(0.688)	(0.227)
λ_{22} (Greek Rating Events)	-0.012	-0.021	-0.011	-0.029	-0.014
	(0.748)	(0.543)	(0.723)	(0.408)	(0.687)
λ_{23} (Bailout Events)	0.250*	0.149	0.113	0.192	0.340**
	(0.099)	(0.253)	(0.382)	(0.164)	(0.023)
α	-0.000	0.000	0.127	0.148***	-0.000
	(1.000)	(0.952)	(0.133)	(0.000)	(1.000)
β	0.999***	0.999***	-0.000	0.966***	-0.997***
	(0.000)	(0.000)	(1.000)	(0.000)	(0.000)
g	-0.000	-0.000	-0.312**	0.118*	-0.000
	(1.000)	(1.000)	(0.036)	(0.066)	(1.000)
v_1 (Domestic Rating Events)	0.185	-0.029**	0.742***	0.070	0.222***
	(0.155)	(0.040)	(0.000)	(0.273)	(0.000)
v_2 (Greek Rating Events)	0.019***	0.015***	0.016	0.024**	-0.001
	(0.000)	(0.000)	(0.784)	(0.048)	(0.884)
v_3 (Bailout Events)	0.027	0.016	-0.101	-0.226***	-0.074**
	(0.433)	(0.401)	(0.648)	(0.002)	(0.043)

Table 4C.6: Full Results of Spillover Effect of Greek Sovereign Rating Events

(Continued)

	Slovenia (E)	U.S.	U.K.
θ_1	0.048***	-0.079***	-0.084***
	(0.000)	(0.000)	(0.000)
γ_{11}	0.056***	0.025***	-0.150***
	(0.000)	(0.000)	(0.000)
γ_{12}	0.103***		
	(0.000)		
γ_{13}	0.079***		
	(0.000)		
γ_{14}	-0.031***		
	(0.001)		
φ_{11}	-0.230***	-0.498***	-0.658***
	(0.000)	(0.000)	(0.000)
φ_{12}	-0.243***		
	(0.000)		
φ_{13}	-0.164***		
	(0.000)		
φ_{14}	-0.108***		
	(0.000)		
δ_{11} (Domestic Rating Events)	0.179	-0.894	-0.129
	(0.361)	(0.695)	(0.756)
δ_{12} (Greek Rating Events)	-0.235**	-0.062***	-0.355***
	(0.019)	(0.000)	(0.000)
δ_{13} (Bailout Events)	-0.903***	1.345	-1.697***
	(0.000)	(0.790)	(0.000)
c_1	-0.064***	0.067***	0.870***
	(0.000)	(0.000)	(0.000)
a_1	0.147***	0.260***	0.303***
	(0.000)	(0.000)	(0.000)
b_1	0.993***	0.916***	0.664***
	(0.000)	(0.000)	(0.000)

d_1		0.099***	-0.017
		(0.000)	(0.493)
λ_{11} (Domestic Rating Events)	0.067	0.314	3.920***
	(0.124)	(0.434)	(0.000)
λ_{12} (Greek Rating Events)	-0.069***	0.056	0.011
	(0.004)	(0.339)	(0.902)
λ_{13} (Bailout Events)	0.158	3.061***	0.460
	(0.145)	(0.000)	(0.526)
θ_2	-0.085***	0.023	-0.011
	(0.000)	(0.193)	(0.583)
γ_{21}	-0.072***	-0.013**	-0.001
	(0.000)	(0.012)	(0.808)
γ_{22}	-0.048***		
	(0.000)		
γ_{23}	-0.056***		
	(0.000)		
γ_{24}	-0.027***		
	(0.000)		
φ_{21}	0.023	-0.050**	-0.013
	(0.231)	(0.031)	(0.594)
φ_{22}	-0.063***		
	(0.000)		
φ_{23}	-0.030		
	(0.243)		
φ_{24}	-0.009		
	(0.698)		
δ_{21} (Domestic Rating Events)	-0.055	0.419	-0.592*
	(0.605)	(0.165)	(0.077)
δ_{22} (Greek Rating Events)	0.021	0.166***	0.075
	(0.659)	(0.002)	(0.158)
δ_{23} (Bailout Events)	0.083**	0.593	-0.626
	(0.045)	(0.437)	(0.713)
c_2	-0.421***	-0.087***	-0.105***
	(0.000)	(0.000)	(0.000)
a_2	0.703***	0.108***	0.139***
	(0.000)	(0.000)	(0.000)
b_2	0.862***	0.976***	0.977***
	(0.000)	(0.000)	(0.000)
d_2		-0.147***	-0.131***
		(0.000)	(0.000)
λ_{21} (Domestic Rating Events)	0.052	-0.766***	-0.014
	(0.720)	(0.001)	(0.969)
λ_{22} (Greek Rating Events)	0.156**	-0.051	0.027
	(0.039)	(0.105)	(0.453)
λ_{23} (Bailout Events)	0.005	0.680***	0.386
	(0.987)	(0.001)	(0.386)
α	0.248***	-0.000	0.000
	(0.000)	(1.000)	(0.999)
β	0.506**	0.993***	0.999***
	(0.012)	(0.000)	(0.000)
g	-0.000	-0.000	0.000
	(1.000)	(1.000)	(0.999)
v_1 (Domestic Rating Events)	0.010	0.206***	0.010
	(0.945)	(0.000)	(0.838)
v_2 (Greek Rating Events)	-0.071	0.040***	0.011***
	(0.179)	(0.000)	(0.000)
v_3 (Bailout Events)	-0.276	-0.373***	-0.104***
	(0.189)	(0.000)	(0.001)

Notes: This table reports the full estimation results of Table 4.12.

EGARCH without asymmetry (E):

$$log\ h_{1t} = c_1 + a_1 \frac{|\varepsilon_{1t-1}|}{\sqrt{h_{1t-1}}} + b_1\ log\ h_{1t-1} + \lambda_{11} Domestic\ Rating\ Events_t + \lambda_{12} Greek\ Rating\ Events_t + \lambda_{13} Bailout\ Events_t$$

$$log\ h_{2t} = c_2 + a_2 \frac{|\varepsilon_{2t-1}|}{\sqrt{h_{2t-1}}} + b_2\ log\ h_{2t-1} + \lambda_{21} Domestic\ Rating\ Events_t + \lambda_{22} Greek\ Rating\ Events_t + \lambda_{23} Bailout\ Events_t$$

ET denotes Student's t EGARCH without asymmetry. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.7: Full Linear Regression Results of Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
α	0.179***	0.087***	0.113***	0.152***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(1.000)
β	0.851***	0.996***	0.993***	0.959***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	-0.181	0.000	0.000	0.000	-0.385***
	(0.247)	(1.000)	(1.000)	(1.000)	(0.007)
ξ_0	-0.419***	-0.513***	-0.564***	-0.270***	-0.077***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	0.004	0.038***	0.065***	0.000	0.005
(Rating Events)	(0.473)	(0.000)	(0.003)	(0.960)	(0.308)
	Germany	France	Netherlands	Belgium	Austria
α	0.101***	0.136***	-0.103***	0.171***	0.172**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.037)
β	0.991***	0.987***	0.993***	0.975***	-0.419
	(0.000)	(0.000)	(0.000)	(0.000)	(0.352)
g	0.000	0.000	-0.107***	0.000	0.225**
	(1.000)	(1.000)	(0.001)	(1.000)	(0.044)
ξ_0	-0.205***	-0.260***	-0.280***	-0.323***	-0.218***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	0.046	0.149**	0.157***	0.084***	0.011
(Rating Events)	(0.702)	(0.012)	(0.009)	(0.007)	(0.432)
	Slovenia	Finland	U.S.	U.K.	
α	0.192***	0.000	0.240***	0.074***	
	(0.000)	(1.000)	(0.000)	(0.000)	
β	0.949***	0.353	0.952***	0.998***	
	(0.000)	(0.419)	(0.000)	(0.000)	
g	0.000	-0.276**	0.000	0.000	
	(1.000)	(0.045)	(1.000)	(1.000)	
ξ_0	-0.100***	-0.233***	-0.118***	-0.208***	
	(0.000)	(0.000)	(0.000)	(0.000)	
ϕ_1	-0.013	0.005	0.041	0.143***	
(Rating Events)	(0.408)	(0.187)	(0.132)	(0.000)	

Notes: This table reports the full estimation results of Table 4.13. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.8: Full Linear Regression Results of Domestic Negative and Positive Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
α	0.176***	0.088***	0.112***	0.1462***	0.144
	(0.000)	(0.000)	(0.000)	(0.000)	(0.110)
β	0.857***	0.996***	0.993***	0.9548***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	-0.175	0.000	0.000	0.0000	-0.305**
	(0.219)	(1.000)	(1.000)	(1.000)	(0.047)
ξ_0	-0.418***	-0.514***	-0.561***	-0.274***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1 (Positive Rating	-0.008	-0.007	-0.053	0.019	0.012
Events)	(0.647)	(0.833)	(0.608)	(0.160)	(0.406)
ϕ_2 (Negative	0.005	0.045***	0.073***	-0.003	0.001
Rating Events)	(0.322)	(0.000)	(0.002)	(0.572)	(0.338)
	Germany	France	Netherlands	Belgium	Finland
α	0.101***	0.139***	-0.102***	0.171***	0.000
	(0.002)	(0.000)	(0.000)	(0.000)	(1.000)
β	0.991***	0.986***	0.993***	0.976***	0.379
	(0.000)	(0.000)	(0.000)	(0.000)	(0.218)
g	0.000	0.000	0.105***	0.000	-0.338***
	(1.000)	(1.000)	(0.001)	(1.000)	(0.007)
ξ_0	-0.205***	-0.259***	-0.277***	-0.324***	-0.233***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1 (Positive Rating	-0.450***	0.000	0.109***	-0.021	-0.014***
Events)	(0.000)	(0.000)	(0.000)	(0.814)	(0.000)
ϕ_2 (Negative	0.145	0.142**	0.211*	0.103***	0.012***
Rating Events)	(0.211)	(0.013)	(0.077)	(0.001)	(0.000)
	U.S.	U.K.			
α	0.237***	0.074***			
	(0.000)	(0.000)			
β	0.954***	0.998***			
	(0.000)	(0.000)			
g	0.000	0.000			
	(1.000)	(1.000)			
ξ_0	-0.119***	-0.206***			
	(0.000)	(0.000)			
ϕ_1 (Positive Rating	0.040	0.181***			
Events)	(0.548)	(0.000)			
ϕ_2 (Negative	0.049***	0.124***			
Rating Events)	(0.000)	(0.000)			

Notes: This table reports the full estimation results of Table 4.14. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.9: Full Linear Regression Results of Domestic Sovereign Rating Surprises

	Austria	Cyprus	France	Ireland	Italy	Spain
α	0.166*	0.000	0.136***	0.153***	0.114***	0.086***
	(0.059)	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.403	-0.248	0.987***	0.958***	0.993***	0.996***
	(0.411)	(0.856)	(0.000)	(0.000)	(0.000)	(0.000)
g	-0.218*	-0.273*	0.000	0.000	0.000	0.000
	(0.058)	(0.069)	(1.000)	(1.000)	(1.000)	(1.000)
ξ_0	-0.215***	-0.073***	-0.260***	-0.269***	-0.573***	-0.516***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1 (Rating	-0.014***	-0.001	0.289***	0.015***	0.089***	0.029
Surprises)	(0.000)	(0.338)	(0.000)	(0.000)	(0.000)	(0.294)

Notes: This table reports the full estimation results of Table 4.15. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.10: Full Linear Regression Results of Bailouts

	Portugal	Spain	Italy	Ireland	Cyprus
α	0.175***	0.088***	0.112***	0.155***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
β	0.922***	0.996***	0.993***	0.955***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	-0.072	0.000	0.000	0.000	-0.397***
	(0.583)	(1.000)	(1.000)	(1.000)	(0.009)
ξ_0	-0.422***	-0.510***	-0.559***	-0.271***	-0.075***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	-0.082**	-0.041	-0.036	-0.023	-0.008***
(Bailout Events)	(0.010)	(0.236)	(0.528)	(0.360)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
α	0.098***	0.135***	0.102***	0.161***	0.167**
	(0.002)	(0.000)	(0.000)	(0.000)	(0.013)
β	0.991***	0.987***	0.993***	0.977***	0.446
	(0.000)	(0.000)	(0.000)	(0.000)	(0.277)
g	0.000	0.000	-0.109***	0.000	-0.188*
	(1.000)	(1.000)	(0.001)	(1.000)	(0.088)
ξ_0	-0.202***	-0.259***	-0.278***	-0.324***	-0.229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	-0.035**	-0.050***	-0.066	-0.122***	0.021*
(Bailout Events)	(0.032)	(0.004)	(0.161)	(0.001)	(0.053)
	Slovenia	Finland	U.S.	U.K.	
α	0.249***	0.000	0.239***	0.070***	
	(0.000)	(1.000)	(0.000)	(0.000)	
β	0.514**	0.415	0.967***	0.998***	
	(0.013)	(0.257)	(0.000)	(0.000)	
g	0.000	-0.338***	0.000	0.000	
	(1.000)	(0.009)	(1.000)	(1.000)	
ξ_0	-0.103***	-0.227***	-0.133***	-0.213***	
	(0.000)	(0.000)	(0.000)	(0.000)	
ϕ_1	-0.018	0.005	-0.039	0.039***	
(Bailout Events)	(0.425)	(0.511)	(0.226)	(0.000)	

Notes: This table reports the full estimation results of Table 4.16. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.11: Full Linear Regression Results of Bailouts and Domestic Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
α	0.177***	0.089***	0.116***	0.150***	0.000
	(0.002)	(0.000)	(0.000)	(0.000)	(1.000)
β	0.902***	0.996***	0.993***	0.960***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
g	0.072	0.000	0.000	0.000	-0.361**
	(0.750)	(1.000)	(1.000)	(1.000)	(0.011)
ξ_0	-0.421***	-0.510***	-0.566***	-0.268***	-0.075***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	0.006	0.038***	0.070***	-0.001	0.004
(Rating Events)	(0.379)	(0.000)	(0.002)	(0.929)	(0.288)
ϕ_2	-0.061**	-0.044	-0.040	-0.019	-0.007***
(Bailout Events)	(0.011)	(0.205)	(0.507)	(0.405)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
α	0.096***	0.135***	-0.090***	0.167***	0.155*
	(0.007)	(0.000)	(0.000)	(0.000)	(0.060)
β	0.992***	0.987***	-0.995***	0.977***	-0.452
	(0.000)	(0.000)	(0.000)	(0.000)	(0.251)
g	0.000	0.000	0.000	0.000	-0.233**
	(1.000)	(1.000)	(1.000)	(1.000)	(0.018)
ξ_0	-0.203***	-0.258***	-0.270***	-0.319***	-0.216***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	0.045	0.150**	0.112***	0.087***	0.008
(Rating Events)	(0.706)	(0.011)	(0.007)	(0.005)	(0.435)
ϕ_2	-0.035**	-0.051***	-0.062*	-0.118***	0.026**
(Bailout Events)	(0.024)	(0.003)	(0.056)	(0.002)	(0.038)
	Slovenia	Finland	U.S.	U.K.	
α	0.189***	0.000	0.231***	0.239***	
	(0.000)	(1.000)	(0.000)	(0.000)	
β	0.946***	-0.402	0.962***	0.822***	
	(0.000)	(0.182)	(0.000)	(0.000)	
g	0.000	-0.340***	0.000	-0.000	
	(1.000)	(0.005)	(1.000)	(1.000)	
ξ_0	-0.101***	-0.233***	-0.125***	-0.160***	
	(0.000)	(0.000)	(0.000)	(0.000)	
ϕ_1	-0.013	0.006	0.046	-0.008	
(Rating Events)	(0.355)	(0.352)	(0.127)	(0.376)	
ϕ_2	-0.008	0.005	-0.043*	-0.076***	
(Bailout Events)	(0.634)	(0.496)	(0.079)	(0.000)	

Notes: This table reports the full estimation results of Table 4.17. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 4C.12: Full Linear Regression Results of Spillover Effect of Greek Sovereign Rating Events

	Portugal	Spain	Italy	Ireland	Cyprus
α	0.196***	0.088***	0.110***	0.276***	0.000
	(0.000)	(0.000)	(0.000)	(0.008)	(1.000)
β	0.643**	0.996***	0.994***	0.000	0.000
	(0.043)	(0.000)	(0.000)	(1.000)	(1.000)
g	0.290**	0.000	0.000	0.000	-0.407***
	(0.023)	(1.000)	(1.000)	(1.000)	(0.004)
ξ_0	-0.421***	-0.510***	-0.560***	-0.247***	-0.076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1 (Domestic	0.001	0.037***	0.065***	-0.003	0.005
Rating Events)	(0.795)	(0.000)	(0.002)	(0.451)	(0.297)
ϕ_2 (Greek	0.000	-0.018***	-0.033***	-0.002	-0.005
Rating Events)	(0.867)	(0.003)	(0.000)	(0.611)	(0.185)
ϕ_3 (Bailout	-0.021*	-0.037	-0.028	-0.007	-0.009***
Events)	(0.061)	(0.300)	(0.622)	(0.848)	(0.000)
	Germany	France	Netherlands	Belgium	Austria
α	0.097***	0.134***	0.101***	0.164***	0.110
	(0.002)	(0.000)	(0.000)	(0.000)	(0.263)
β	0.993***	0.987***	0.993***	0.978***	-0.557
	(0.000)	(0.000)	(0.000)	(0.000)	(0.160)
g	0.000	0.000	-0.108***	0.000	0.221**
	(1.000)	(1.000)	(0.001)	(1.000)	(0.017)
ξ_0	-0.199***	-0.258***	-0.280***	-0.317***	-0.220***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1 (Domestic	0.030	0.150**	0.158***	0.086***	0.004
Rating Events)	(0.798)	(0.011)	(0.007)	(0.005)	(0.425)
ϕ_2 (Greek	-0.001	-0.002	-0.019**	0.004	-0.002
Rating Events)	(0.942)	(0.818)	(0.039)	(0.689)	(0.371)
ϕ_3 (Bailout	-0.028*	-0.051***	-0.066	-0.102***	0.017**
Events)	(0.066)	(0.003)	(0.168)	(0.005)	(0.036)
	U.S.	U.K.			
α	0.219***	0.223***			
	(0.000)	(0.000)			
β	0.963***	0.843***			
	(0.000)	(0.000)			
g	0.000	-0.000			
	(1.000)	(1.000)			
ξ_0	-0.125***	-0.158***			
	(0.000)	(0.000)			
ϕ_1 (Domestic	0.025	-0.016**			
Rating Events)	(0.299)	(0.018)			
ϕ_2 (Greek	-0.004	0.007*			
Rating Events)	(0.503)	(0.064)			
ϕ_3 (Bailout	-0.037*	-0.062***			
Events)	(0.090)	(0.000)			

Notes: This table reports the full estimation results of Table 4.18. The p-values of the coefficients are in the parentheses. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Appendix 4D: Sy's (2004) CCR Coding Method

Table 4D.1: Comprehensive Credit Rating Definition of Sy (2004)

Explicit Credit Rating (ECR)				Credit Outlook/Watchlist	
S&P	Moody's	Fitch	Numerical code	Information	Add to ECR
AAA	Aaa	AAA	58	Positive	1
AA+	Aa1	AA+	55	CW-Pos	2
AA	Aa2	AA	52	Stable/CW-Dev	0
AA-	Aa3	AA-	49	CW-Neg	-2
A+	A1	A+	46	Negative	-1
A	A2	A	43		
A-	A3	A-	40		
BBB+	Baa1	BBB+	37		
BBB	Baa2	BBB	34		
BBB-	Baa3	BBB-	31		
BB+	Ba1	BB+	28		
BB	Ba2	BB	25		
BB-	Ba3	BB-	22		
B+	B1	B+	19		
B	B2	B	16		
B-	B3	B-	13		
CCC+	Caa1	CCC+	10		
CCC	Caa2	CCC	7		
CCC-	Caa3	CCC-	4		
CC/C	Ca/C	CC/C	1		
SD/D		RD/D	0		

Notes: This table shows Sy's (2004) CCR coding method. CW-Pos denotes Credit Watch-Positive, CW-Dev denotes Credit Watch-Developing, and CW-Neg denotes Credit Watch-Negative.

Table 4D.2: Sovereign Credit Rating Events of Sy's (2004) Method

Country	No. of rating events	No. of Negative rating events	No. of Positive rating events
Austria	6	5	1
Belgium	13	9	4
Cyprus	44	31	13
Finland	7	5	2
France	10	10	0
Germany	4	4	0
Greece	56	42	14
Ireland	37	22	15
Italy	16	14	2
Portugal	33	24	9
Spain	31	23	8
Slovenia	24	19	5
Netherlands	8	4	4
US	5	3	2
UK	4	3	1
Total	298	218	80

Notes: This table reports the total number of sovereign credit rating events and the numbers of positive and negative rating events in each examined country by using Sy's (2004) CCR coding method.

Chapter 5: Conclusion

5.1 Summary of the Findings and the Implications

This thesis investigates three issues related to the informational role of CDS from the perspectives of discovering credit risk news and directly indicating market expectation of the credit risk of the underlying reference entity. Chapter 2 investigates credit risk discovery between CDS and stock of the U.S. non-financial firms. Chapter 3 studies credit risk connectedness across multinational systemically important financial firms. Chapter 4 examines the impact of sovereign default risk events on sovereign CDS and equity index in major developed economies. In this section, the major findings of each empirical study are summarised and the implications of the findings are discussed.

Chapter 2 uses Lien and Shrestha's (2014) generalised information share (GIS) because CDS spread and the implied credit spread from stock price may not satisfy the one-to-one cointegration relation assumed by Hasbrouck's (1995) information share (IS) and Gonzalo and Granger's (1995) component share (GG). By comparing the results of GIS and that of IS and GG, this chapter contributes to the current understanding of GIS, e.g., Shrestha (2014), by showing that at least in the case of two assets, GIS may not alter empirical results substantially even though it is theoretically stronger than IS and GG. Second, this chapter documents that the stock market generally leads the CDS market in incorporating credit risk news, which is in line with several previous literature, e.g., Forte and Peña (2009). However, similar to Xiang et al. (2013), over the crisis period of 2008–2010, the CDS market is found to dominate the stock market. This chapter also finds that in the U.S., eliminating transitory components from CDS quotes and stock prices has a relatively greater impact on the informational efficiency of CDS and stock markets in the earlier sample period. This complements the study of Forte and Lovreta

(2015) who discuss the similar issue in the European markets. Moreover, this chapter extends the existing understanding of the determinants of credit risk discovery process of CDS and stock markets. The more stressful the economy condition is, the more credit risk discovery the CDS market contributes. An increased funding cost is accompanied with a decline of the credit risk discovery contribution of CDS. The central clearing counterparty (CCP) in the CDS market cannot strengthen this market's informational efficiency and transparency.

Overall, the findings of Chapter 2 bear some important implications for the researchers, investors, and policymakers. For example, the more robust price discovery contribution techniques may not necessarily provide qualitatively different conclusions in credit risk discovery research. The CDS market provides price discovery over the crisis times. The negative impact of funding cost on credit risk discovery of CDS implies that similar to financing cost, any factor which influences investors' trading decisions may also affect the informational efficiency of CDS, which may inspire further research. Also, the CDS market seems to have a higher proportion of insiders; thus, introducing central clearing service may not practically improve market efficiency and transparency. Policymakers may need to ameliorate the CCP policy and rethink about how to effectively introduce CCP in the other OTC markets which are similar to the CDS market.

Chapter 3 uses Diebold and Yilmaz's (2015a) connectedness measures based on VECM model to study the transmission of credit risk across a special group of financial firms, the designated G-SIFIs, from 2006 to 2014. It extends the existing understanding of credit risk transmission across financial institutions by indicating that the total credit risk connectedness (CRC) across G-SIFIs significantly increases since mid-2006 and moves around a relatively high level, 90%, until the end of 2014. Unlike Diebold and

Yilmaz (2015a), we find that the empirical results of the VECM-based connectedness measures and that of the VAR-based connectedness measures are qualitatively similar. This implies that although the VECM model may account for the cointegration relations, it may not suggest different results in empirical applications. To quantify to what extent the total CRC of G-SIFIs would threaten the global financial stability, we compute a scored CRC (Z_{CRC}). The peaks of Z_{CRC} (larger than 2) generally indicate the critical financial events in the sample period. Moreover, in contrast to the G-SIFIs from Europe or Asia, the G-SIFIs from the U.S. are major credit risk senders. Although bidirectional credit risk spillovers between G-SIBs and G-SIIs are found, G-SIBs are generally credit risk providers. Based on dynamic net directional credit risk spillovers of each G-SIFI, we provide a yearly 'Too-interconnected-to-fail' ranking. This ranking complements the official list released by the FSB since our ranking is derived directly from the CDS market data. The two lists can be combined together to design a 'composite' ranking which considers not only market judgement of G-SIBs' credit risk importance, but also G-SIBs' general business risk importance. Finally, it extends the current understanding of the factors explaining the role of financial firm in credit risk transmission, e.g., Yang and Zhou (2013). It finds that interbank lending, non-interest income (especially trading account income), and extra capital surcharge are positively related to G-SIBs' systemic credit risk importance. The Tier 1 leverage ratio or leverage ratio may help lower the G-SIBs' credit risk spillovers, whereas the situation is opposite for Tier 1 capital ratio or capital adequacy ratio. The G-SII with more non-traditional non-insurance activity, larger size, and more global sales is more systemically relevant.

Overall, the results of Chapter 3 yield important insight into credit risk transmission across the designated G-SIFIs and bring forward several suggestions to the worldwide regulatory authorities. For instance, it is crucial for regulators to assess the sources and directions of credit risk transmissions among the important financial institutions, so that they can deepen their understanding about the complex structure of risk connections among the financial firms. Also, regulators can adopt the scored CRC to timely monitor any abnormal and destructive increase in credit risk spillovers among the G-SIFIs, so that they can take prompt actions to maintain the global financial stability. Moreover, the ‘composite’ ranking suggests an innovative and simple approach for regulators to devise a more comprehensive methodology to identify G-SIBs or even G-SIIs. Last but not least, the discovered factors driving G-SIFIs’ credit risk transmission may provide regulators insight into how to design more effective policies to reduce the systemic risk posed by G-SIFIs, such as make further efforts to refine the design and implementation of the Basel III Tier 1 leverage ratio requirement.

Chapter 4 applies ADCC-X model to extend the existing understanding of the impact of sovereign rating events and major bailout news on returns, volatility, and correlation of sovereign CDS and equity index in the U.S., the U.K., and the Eurozone states during the relatively turbulent period of 2008–2016. It adopts a more general measure of sovereign rating events and computes rating surprises, which complements Gande and Parsley (2005) and Drago and Gallo (2016). The results show that compared with equity market, sovereign CDS market is more sensitive to domestic rating events or surprises. Two assets become less correlated when rating events/surprises occur. Both asymmetric and symmetric impact exerted by good and bad rating events on returns and volatility of individual assets is found, as well as correlation. Symmetric impact of two rating news on asset correlation is found in Spain, Italy, and Cyprus. In Portugal, Netherlands, and the U.S., the two assets are more (less) negatively correlated on the release days of bad (good) rating news, but the opposite situation exists in Ireland and Finland. Good rating news generally presents stronger impact. Major bailout events increase sovereign

CDS returns and reduce equity returns. Asset volatility raises and two assets are more correlated. In contrast with domestic rating events, bailout news has more pronounced impact on not only individual assets, but also asset correlation. These above findings provide further supports to Andersen et al. (2007) and Brenner et al. (2009) who suggest that asset correlation can be driven by the releases of macro events. Finally, this chapter contributes to the extant literature of the spillover effect of sovereign rating events, e.g., Ismailescu and Kazemi (2010), by showing that Greek sovereign rating events have information spillover effect on the two assets in several sample countries. The negative correlation increases along with the arrival of Greek rating news. Equity investors seem to concern more about Greek rating changes than domestic rating events.

International portfolio managers and policymakers may find valuable implications from the results of Chapter 4. For example, unlike the investors in sovereign CDS market, investors in equity market seem to pay less attention to domestic sovereign rating events. It suggests that in equity market, at least after 2008 and in the sample states, domestic sovereign rating events may not be as informative as highlighted by previous studies. It may also reveal the tendency of investors to reduce overreliance on sovereign rating information provided by rating agencies. Given the criticisms about rating agencies, the FSB (2010) requires institutional investors, regulators, and banks to reduce overreliance on external rating agencies and to have own evaluations of their credit risk exposures. More importantly, our results suggest that the announcements of major bailouts exert destabilising impact on both sovereign CDS and equity markets through reducing asset returns and increasing asset volatility. Abnormal cross-asset trading activities may exist at the arrival of bailout news, since the two markets become more correlated. As widely agreed by international policymakers, bailouts could not be a priority to guarantee the resilience and stability of domestic or regional financial system.

5.2 Limitations and Further Research

This thesis can be improved in several ways. First, in Chapter 2, due to data availability, there are 113 non-financial companies from the U.S. in the sample. This small sample problem may be addressed if we have the access to more CDS market data. Second, Chapter 3 focuses on CDS return spillovers across the designated G-SIFIs. However, Diebold and Yilmaz's (2014) connectedness measures can also be used to investigate volatility spillovers by employing volatility as dependent variables of VAR or VECM model. To obtain volatility, non-parametric approaches are usually used, such as range-based volatility and realised volatility (Diebold and Yilmaz, 2009, 2012, and 2014). However, these methods require intraday market information. Due to the thin intraday trading problem of single-name CDS (Chen et al., 2011) and data scarcity, this chapter cannot obtain sufficient information to calculate CDS volatility. Finally, to ensure that the ADCC-X model is relatively parsimonious, Chapter 4 focuses only on the news announcement days and does not consider the days before and after the news releases. Previous studies have shown that before and after news releases, financial markets can also have reactions, e.g., Brenner et al. (2009). Therefore, it may be better to consider these two periods.

Besides the above limitations, several further research agenda could be pursued. First, whether CCP exerts impact on CDS contracts of European firms has not been explored. Further research can investigate this issue from several aspects, such as market liquidity, counterparty risk, credit risk discovery, etc. Also, all the price discovery measures used in Chapter 2 are based on linear cointegration framework and rolling-window method is used to obtain the time-varying price discovery contributions. However, as suggested by Cai et al. (2011, 2015) and Ngene et al. (2014), price discovery process may be state or regime dependent. Thus, it is also important to study credit risk discovery mechanism in a nonlinear cointegration framework. Second, on March 4, 2015, the FSB and the International Organization of Securities Commissions (IOSCO) proposed to identify the third group of G-SIFIs which includes non-bank non-insurer financial firms (NBNI G-SIFIs), such as large hedge funds and important asset management firms. Therefore, further study can analyse credit risk transmission across the existing G-SIFIs and the newly identified NBNI G-SIFIs to provide a more comprehensive 'too-interconnected-to-fail' ranking. Finally, while sovereign default risk of major developed countries has drawn much attention since the European sovereign debt crisis, sovereign credit risk of emerging markets remains important. Market microstructures, regulatory policies, and levels of investor sophistication widely vary across two types of economies. Hence, it may be a promising research topic to investigate news impact of sovereign rating events, political shocks, and other macro events on the correlation between sovereign CDS and equity index in emerging countries. Also, although the GARCH-type models have the merit of revealing volatility persistence, they may fail to identify the directions of the interactions across assets (Cai et al., 2016). Therefore, the final suggestion for future research is to use a nonlinear Markov switching framework to study the directional and dynamic causality relationship between the returns of sovereign CDS and equity index in both advanced and emerging economies.

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