ESSAYS ON SYSTEMIC RISK AND RISK SPILLOVERS

by

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A thesis submitted to the University of Birmingham
for the degree of DOCTOR OF PHILOSOPHY

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November 2016

Abstract

This thesis studies the implications of risk spillover effects in the systemic risk regarding financial institutions and financial system. In Chapter 3 we study the risk spillovers from sovereign CDS market to financial CDS market and the systemic risk contributions of sovereign countries, by using the $\Delta CoVaR$ risk measure. In Chapter 4, using a high dimensional $GVAR$ model, we then extend the previous study to investigate the dynamics of sovereign risk spillovers to the sovereign bond market, sovereign CDS market, and the national banking sectors, and we examine the interdependence of these markets. Lastly in Chapter 5, we constuct the tail-dependence network for the risk spillovers of global financial institutions and study the implications of network interconnectedness of the financial institutions as well as its contributions to systemic risk.

Our research provides further understanding regarding the systemic risk and risk spillovers. In particular, regarding sovereign risk spillovers to the financial system, we find evidence regarding the different roles of state intervention measures in influencing the risk spillovers, and the spillover impact from Italy and Spain impose great stress to the financial stability. In addition, we find that the interconnectedness of the tail returns of financial institutions, which is deeply under the influence of common market conditions, contribute more to the financial systemic risk than the initial events of risk spillovers.

To my parents.

Acknowledgements

I thank my supervisor Professor David Dickinson for his guidance in my studies. My research has benefited from his great knowledge and invaluable advice. I am also indebted to my supervisor Nicholas Horsewood for his continuous support.

I thank Rong Huang for her tremendous support and care all these years, without which I would not make it this far. I also would like to express gratitude to all my friends and colleagues for their kind support. I am also grateful to all the literature and studies from which my research greatly benefit from, and all the scientific and technological communities from where I have learned the most invaluable knowledge.

My deepest gratitude to my parents for their love.

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List of Abbreviations

AIG .... American International Group

BIS .... the Bank of International Settlements

CDS .... credit default swaps

ECB .... European Central Bank

EMU .... the European Monetary Union

EU .... the European Union

FSB .... the Financial Stability Board

GDP .... Gross Domestic Product

IMF .... International Monetary Fund

NBER .... National Bureau of Economic Research

OECD .... the Organisation for Economic Co-operation and Development

TARP .... Troubled Asset Relief Program

UK .... the United Kingdom

US .... the United States of America

ADF .... Augmented Dickey-Fuller test (Dickey and Fuller, 1979)

AIC .... Akaike information criterion (Akaike, 1976)

$CoVaR$ .... Conditional Value-at-Risk (Chernozhukov and Umantsev, 2001; Adrian and Brunnermeier, 2011)

DIP .... Distress Insurance Premium (Huang, Zhou and Zhu, 2012*a*)

$FEVD$ .... Forecast error variance decomposition (Pesaran and Shin, 1998)

$GIRF$ .... Generalised impulse response function (Pesaran and Shin, 1998)

$GVAR$ .... Global Vector-Autoregressive model (Pesaran, Schuermann and Weiner, 2004)

$LASSO$ .... the Least Absolute Shrinkage and Selection Operator Method (Tibshirani, 1996)

LGD .... Loss given default

MES .... Marginal Expected Shortfall (Acharya, Engle and Richardson, 2012)

PD .... Probability of default

VAR .... Vector-Autoregressive model (Sims, 1980)

VEC .... Vector error correction model (Engle and Granger, 1987)

VaR .... Value-at-Risk (Leavens, 1945)

Chapter 1

Introduction

1.1 Recent development in Systemic Fragility

The global financial sector in the last decade has been characterised by the occurrence of several financial crises, which puts into question the stability and resilience of the domestic, regional, and global financial system. The Subprime Crisis in 2007 originated from the financial institutions' excessive exposure to the subprime mortgage market, which leads to distress and default of market participants. And self-reinforced exacerbation of risk sentiment and market liquidity led by the persistence of market distress, together with an arguably less resilient system structure, resulted in the swift drying up of market liquidity and the collapse of several high profiled financial institutions which triggered the Global Financial Crisis of 2008-2009 and the recessions of many national economies. National authorities sought to stabilise the domestic financial markets and boost economic growth with massive bailout packages, which in various ways transferred the distress burdens from the private sectors to the balance sheets of national governments. The sudden accumulation of fiscal burden, combined with pessimistic prospect of economic growth and the deep-rooted problems in economic structures, resulted in a credibility crisis regarding the fiscal sustainability in several sovereign countries in the European Sovereign Crisis of 2010-2012. Although these crisis episodes share some commonality in the amplification of the initial impact, the self-reinforced transmission and propagation of risk impact, and the rapid freezing of institutional lending and market liquidity, they are triggered from various sources but with spillover effects converged to form massive destabilising events that endanger financial stability.

Although the inherent fragility of the financial system with has been widely acknowledged (Diamond and Dybvig, 1983; Bhattacharya and Gale, 1985; Allen and Gale, 2000), recent development in the financial institutions adds new element to the financial fragility. Financial institutions are becoming more homogenous in the sense that the distinction among commercial banks, broker-dealers, and insurers is blurred with each market participants expanding their business lines to different territories. They are also more reliant on the wholesale funding markets of inter-institutional borrowing and lending. An increasing homogenous financial system means the risk impact from a single source is now easier to reach any market participants at a more rapid speed. In addition, a more densely interlinked financial system provide the breeding environment for the emergence of financial institutions that take advantage of the "too-interconnected-to-fail" problem, exacerbating the fragility of the financial systems.

The systemic risk[1] regarding the financial system, regarding the financial institutions, or regarding a specific source of risk impact, has been gaining the attention from academic researchers and policy-makers as an important topic in the development of economic and financial theories, as well as a practical issue in the policy decisions regarding the regulation of the financial system.

[1]The concept will be discussed in Section 2.1.

1.2 Motivation and Outline of the Thesis

1.2.1 Research Objectives

The purpose of our research is to investigate the several issues (to be discussed in Chapter 2) that emerge in the recent development of the financial system regarding the systemic risk of financial institutions:

- We seek to examine the implications of risk spillovers to the systemic risk:
  - The impact of sovereign risk spillovers to financial institutions.
  - The driving force of sovereign risk spillovers and its underlying dynamic effects.
  - The impact of risk spillovers from the interconnectedness of financial institutions.
- We also seek to examine how systemic risk can be measured in adequate ways:
  - How individual sources of risk and their spillover effects can be represented from the perspective of financial stability.
  - How the spillovers from the distress of sovereign countries are reflected in the financial markets and financial institutions.
  - How to assess the interconnectedness in the financial network.

1.2.2 Outline

We carry out several studies addressing certain aspects of the research questions.

In Chapter 2, we discuss the background of our research, including the concepts in systemic risk and its various sources and propagation mechanisms. Specifically, we discuss how systemic risk and its spillovers are measured, and the two sources of systemic risk, sovereign risk and network risk, from which we conduct our research later on. We also provide literature surveys on the previous studies in the specific topics surrounding these issues, which are theoretical and technical foundations of our research.

In Chapter 3, we study the risk spillover effects from sovereign credit risk to financial institutions, using sovereign credit default swaps (CDS) spreads and financial CDS spreads as indicators of credit risk in the two markets. Based on the previous literature on measuring systemic risk in the financial markets, we use the $\Delta CoVaR$ method from Adrian and Brunnermeier (2016) and apply the method to model the risk spillovers from CDS spreads. The systemic risk contributions of a sovereign country is gauged by the overall $\Delta CoVaR$ spillovers to the systemically important financial institutions in our sample. The risk spillovers of $\Delta CoVaR$ estimated from the quantile regression model of Koenker and Bassett Jr (1978) allows us to evaluate its impact in a given time period. To assess the structural stability of the risk measures, we apply the quantile structural test from Qu (2008); Oka and Qu (2011).

Extending our study on sovereign risk spillovers from Chapter 3, in Chapter 4 we study the systemic risk contributions of the risk spillovers of sovereign countries by modelling the dynamics of sovereign distress and the impact to the sovereign bond markets, the sovereign CDS markets, and the national banking sector. We use the Global Vector-Autoregressive ($GVAR$) model which allows for the high dimensional modelling of variable interactions under domestic, regional and global settings. We investigate the impact of shocks from debt burden and the slowing down of economic growth to the various markets and examine the inter-dependence of these markets.

In Chapter 5, we study how the interconnectedness of financial institutions contribute to the systemic risk and its propagation in the financial system. We examine the tail-dependence of the market returns of financial institutions in order to investigate the propagation of risk impact from the distress of one financial institutions to other market participants. We then investigate how the tail-dependence of financial institutions has evolved during the previous episodes of financial crises and market distress events. In addition, we examine the implications of network interconnectedness in terms of how it affects the impact of systemic risk realisation.

Lastly, in Chapter 6, we summarise the findings in our research with its policy implications, and discuss the limitations in our research and research opportunities.

1.3 Contribution

1.3.1 Chapter 3: Systemic Risk Spillovers – Evidence from CDS Market

CDS has been documented as a good indicator of the credit risk of both financial institutions (Huang, Zhou and Zhu, 2012*b*) and sovereign countries (Pan and Singleton, 2008). Our measure of the risk spillovers from the sovereign CDS market to the financial CDS market using $\Delta CoVaR$ allows us to provide both a cross-sectional comparison of the systemic riskiness of sovereign countries as well as an evaluation of the evolutions of the spillover relationships over the time horizon. If there is a large risk spillovers from the contingent default of a sovereign country then this event is likely to cause huge disruption and distress in the financial system, the economic and welfare impact of which should be taken into account when assessing whether there should be a financial support to the distressed country, or to what extent should the support be. In addition, Our examination on the structural stability of the quantile-estimated $\Delta CoVaR$ is the first study to apply a quantile-based structural break test to assess the structural stability of the risk measure and our results provide insights into the structural stability of the quantile-based family of risk measures that has been gaining popularity among researchers and regulators. Lastly, we investigate how the systemic risk contributions of sovereign countries can be explained by the macro-financial fundamentals of the sovereign countries and their involvement in different government intervention schemes, which complements the studies on the determinants of CDS spreads and its component structure (Duffie, Pedersen and Singleton, 2003; Longstaff, Pan, Pedersen and Singleton, 2011).

1.3.2 Chapter 4: Examining Cross-border Sovereign Distress Spillovers

We extend the evidence of risk spillovers from CDS markets in Chapter 3 to sovereign bond markets and the national banking sectors, as well as discuss the multiple scenarios of sovereign distress. The modelling of sovereign risk spillovers in the *GVAR* model of Pesaran et al. (2004); Dees, Mauro, Pesaran and Smith (2007) offers a rigorous way to investigate the impact from sovereign risk to the financial markets. The techniques of impulse response functions and forecast error variance decompositions provide insights into the dynamics of risk spillovers from sovereign risk to various markets and assess the impact over the time horizon, as well as the decomposition of influence from risk origins. In this way we contribute to the understanding of how the financial market distress can be caused by the distress of sovereign countries. Our results offer empirical evidence to the theoretical models on sovereign risk spillovers (Drechsler, Acharya and Schnabl, 2011) and contribute to the study of risk spillovers between markets (Diebold and Yilmaz, 2009; De Bruyckere, Gerhardt, Schepens and Vander Vennet, 2013) from a macro-financial perspective.

1.3.3 Chapter 5: Systemic Risk Spillovers in Tail-Dependence Network

From the perspective of pairwise risk spillovers, we extend the traditional systemic risk measures of market series into the study of financial networks. Specifically, our network extensions of $\Delta CoVaR$ of Adrian and Brunnermeier (2016) incorporate the interconnectedness of financial institutions by their tail-dependence. In addition, our implementation of rolling window models to investigate the time-varying structure of the tail-dependence network which allows us to assess the impact of different crisis periods to the financial network and systemic risk. While previous studies on the tail-dependence network of market series are often limited by the sample size of the pairwise relationships, we contribute to the literature of tail-dependence network (Billio, Getmansky, Lo and Pelizzon, 2012; Hautsch, Schaumburg and Schienle, 2012; Härdle, Wang and Yu, 2016) by considering a larger sample size of pairwise relationships of commercial banks, broker-dealers, and insurance companies in the global financial systems. Our investigations on the topological characteristics (such as the centrality measures of nodes) of the network system also contribute to the further understanding of financial network theory in terms of how the interconnectedness of financial markets should be measured and how resilient the financial system can be to the interconnectedness risk.

Chapter 2

Background of the Research

2.1 Concept and Theory of Systemic Risk

2.1.1 Defining the Concept

We summarise the definitions and concepts regarding "systemic risk" discussed in previous survey literature in Table 2.1. With the definitions in the literature, here we refer to systemic risk as the risk that undermines the financial stability which results in heavy losses in the economy and social welfare. Financial instability undermines the process of financial intermediation, and distress of the financial system causes negative externality to other economic systems, and thus the severe impact of which warrants efforts to safeguard financial stability and contain systemic risk. For example, in the database for banking crises from 1970 to 2009 organised by Laeven and Valencia (2010), the authors estimate that the Global Financial Crisis costs output losses for various sovereign economies: 25% GDP loss for the United States, 24% for the United Kingdom, 39% for Spain, and so on. The two most important elements of systemic risk are its sources and its propagation mechanisms.

Table 2.1: Definitions and Concepts of Systemic Risk in Survey Literature

De Bandt and Hartmann (2000)
• The risk associated with systemic events. • Systemic events can be triggered by idiosyncratic shocks or systematic shocks • Systemic events are characterised by the propagation of initial impact.
European Central Bank (2010)
• The risk of experiencing a systemic event. • Systemic events are events that lead to the impairement of the financial intermediation process and the losses of economic growth and welfare.
Allen and Carletti (2012)
• Types of systemic risk: 1. Common exposures to asset bubbles; 2. Liquidity shocks of price volatility 3. Panics and bank runs 4. Contagion; 5. Sovereign default; 6. Currency shocks.
Bisias, Flood, Lo and Valavanis (2011)
• No single clear common definition yet, as systemic risk can be attributed to many aspects. • “Systemic risk may be hard to define but they[regulators] know it when they see it.”
Benoit, Colliard, Hurlin and Pérignon (2016)
• Systemic risk can be minimally defined as the risk that many market participants are simultaneously affected by severe losses, which then spread through the system.

2.1.2 Sources of Systemic Risk

Here we follow the approach of Smaga (2014) and define two categories of risk sources: endogenous sources and exogenous sources. Endogenous sources refer to the risks triggered within the financial market and exogenous sources are the risks triggered in other sectors of the economy.

Endogenous Sources

The endogenous sources often concern with financial institutions risk taking behaviours, which are usually associated with moral hazard problems. As noted by Adrian and Brunnermeier (2016), initial excessive risk-taking of financial institutions during the build-up period of systemic events generates the first component of systemic risk. The risk of correlated exposure in financial institutions is one such endogenous sources. Bhattacharya and Gale (1985) discusses the free-riding problem of banks over-investing in illiquid assets as banks can rely on the common pool of the interbank market for liquid assets, which lead to a market-wide shortage of liquid assets thus making all banks vulnerable to liquidity shocks.

"Systemically important financial institutions" (SIFIs) is a related concept, where a financial institution[1] is considered systemically important if its distress or failure can be expected to trigger a systemic event. The concerns of regulators and policy-makers regarding SIFIs includes how these institutions should be regulated, how to designate one institution to be systemically important, as well as how to prevent market participants from becoming "too-systemically-important-to-fail" in the system.

[1]The Financial Stability Board currently recognises 30 banks/bank holding companies, and 9 insurance companies to be systemically important, the details of which are listed in Table 5.13 and Table 5.12.

Exogenous Sources

Researchers have been long studying the inherent fragility of the financial systems, however the recent evidence regarding financial crisis documents the importance of external sources of macroeconomic risk. The collapse of US securitised mortgage market in 2007 not only create massive losses to financial institutions, but also reveal many problems in these institutions which result in a general loss of confidence in the market by market participants. The asset bubbles and the bursting of them in real estate sector has been documented to be an important destabilising factor to the financial system, by Allen and Carletti (2009) for economies like the US, Spain and Ireland. Before the Eurozone Sovereign Crisis, the systemic effects of sovereign risk spillovers, in terms of the ways of impacting the financial sector as well as other economic sectors, as noted by Gray (2009), are largely unexplored.

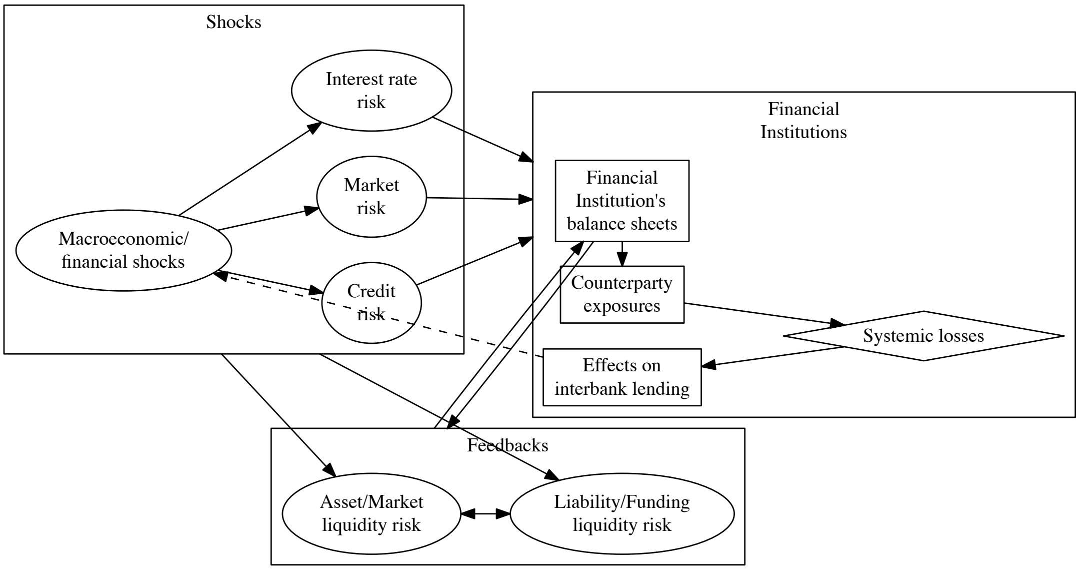

Figure 2.1: Elements of Systemic Risk

Source: based on Aikman et al. (2009)

2.1.3 Propagation Mechanisms of Systemic Risk

Counterparty Exposures

The most intuitous propagation mechanism of systemic risk concerns with counterparty exposures. Consider the simplified case of an interbank cross-holding network of lending/borrowing relationships. The initial failure of a bank due to its asset losses exceeding its capital reserve could lead to the losses of its creditor banks. Losses then propagate to other banks through the mutual lending/borrowing relationships as long as some banks face distress in the propagation process. Studies in the interbank market argue that the impact of such propagation would be limited when financial institutions can fully diversify its counterparty exposures, when there exists a complete network of mutual lending relationships so that the initial impact is diversified away (Freixas, Parigi and Rochet, 2000; Allen, Babus and Carletti, 2012). However, studies in financial network theory show that the stability of the counterparty exposure network will be ultimately determined by the magnitude of the initial impact, and when such impact is sufficiently large enough, the direct linkages of counterparty exposures will serve as a destabilising factor of financial stability (Elliott, Golub and Jackson, 2014; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015).

Fire-sales

Market signals of individual distress and fire-sales of assets, as well as market-wide price increase of credit risk can all lead to indirect losses of external assets of market participants. The fire sale of the assets of a distressed institution leads to negative impact on their prices, which in turn results in a negative impact on other institutions with similar exposures, and impose systemic vulnerability to other institutions. Brunnermeier (2009) discusses the interaction between the "loss spiral" of fire-sales and the "margin spiral" of margin requirements, when losses in assets and depletion of liquidity prompt higher margin requirements by market participants which in turn not only exacerbates the pressure on asset prices but also spreads the contagion to other asset classes. In addition, the signal of fire-sales creates a coordination problem as it prompts institutions to liquidate their positions out of the fear that asset prices will be depressed by other institutions (Lagunoff and Schreft, 2001). As discussed in Haldane and May (2011) and Benoit et al. (2016), in contrast to the form of propagation via mutual debt holding where the impact attenuates due to sufficient diversification of initial impact, the impact of propagation via external asset losses amplifies when more and more individuals are involved in the process, leading to a self-reinforced loss of confidence in the market.

Liquidity Freeze

Another propagation mechanism takes the form of the freeze in funding liquidity, or "liquidity hoarding". As the evidence in the recent episodes of Global Financial Crisis and the Eurozone Sovereign Crisis shows, interbank lending market and repo market suffer substantially when transaction activity slow down and liquidity quickly dry up as financial institutions fear their own exposures to others which in turn exacerbates the impact of the initial distress signal. As discussed in Brunnermeier (2009) and Caballero and Simsek (2013), one of the contributing factor is a "gridlock risk" that financial institutions have no full information regarding the risk position of the counterparties of their counterparties along the direct route of exposure impact, and therefore stop their mutual lending after severe shocks. Solvent but illiquid financial institutions thus need the support from a lender of last resort to prevent them from distress.

However, it is important to note that systemic risk propagation rarely takes a specific form, but rather the combination of several channels reinforcing each other. As argued in Longstaff (2010), there is a significant distinction between the 2007 Subprime Crisis and the 2008 Global Financial Crisis that the Subprime Crisis is characterised by a "credit-risk-induced illiquidity" phenomenon, while the Global Financial Crisis is characterised by a "illiquidity-induced credit risk" phenomenon.

2.2 Measuring Systemic Risk in Financial Market

There are generally three broad categories of measures[2] regarding the systemic risk contributions of financial markets, as well as their exposures to systemic risk, namely statement-based measures which mainly rely on the financial statement information

[2]Many studies, though favouring one approach to the others, often combine elements from all categories of risk measures.

Table 2.2: Literature Strands on Systemic Risk

Diamond and Dybvig (1983); Bhattacharya and Gale (1985); Allen and Gale (2000)
• Theoretical studies on contagion in the financial market. • Financial fragility: in the absence of full information, (bank) runs can be self-fulfilling and self-reinforcing.
Bisias, Flood, Lo and Valavanis (2011); Benoit, Colliard, Hurlin and Pérignon (2016)
• Literature surveys on the theories and applications of systemic risk.
Adrian and Brunnermeier (2011); Huang, Zhou and Zhu (2012*b*); Acharya, Engle and Richardson (2012); Brownlees and Engle (2012)
• Theoretical/empirical frameworks for systemic risk measurement.
Alessandri, Gai, Kapadia, Mora and Puhr (2009); Drechsler, Acharya and Schnabl (2011)
• Theorectial frameworks on sovereign risk spillovers to the financial system.
Gai and Kapadia (2010); Acemoglu, Ozdaglar and Tahbaz-Salehi (2015); Elliott, Golub and Jackson (2014)
• Theoretical frameworks on the financial interconnectedness and systemic risk.

from institutions, market-based measures where the main sources of information are obtained from market series, and network-based measures. Network-based risk measures are generally extensions of the former two categories with the incorporation of network information. Network extensions of statement-based measures examine the mutual exposures of financial institutions and the cascading effect of defaults, whereas network extensions of market-based measures incorporate the network interactions of market series into the risk measures. We focus on the comparisons between statement-based measures and market-based measures in Section 2.2 and leave the discussion of variants of network-based measures in Section 2.4.

2.2.1 Market-based Systemic Measures

As discussed in Acharya, Pedersen, Philippon and Richardson (2010), Bisias et al. (2011) and Benoit et al. (2016), market-based systemic measures have been gaining popularity by researchers and policy-makers since the outbreak of the Global Financial Crisis. Lehar (2005) extends the contingent claim analysis of Merton (1974) with the probability of a systemic event of simultaneous defaults calculated from the correlation of banks' portfolios, which is later adopted in Gray, Merton and Bodie (2008) for a regulatory framework regarding systemic macro-financial risks. Huang et al. (2012*a*,*b*) construct a distress insurance premium (DIP) framework based on the aggregate systemic risk measures calculated from equity return correlations and CDS spreads, for the Asian-Pacific financial system (Huang et al., 2012*a*) and the US financial system (Huang et al., 2012*b*). Based on earlier studies on Conditional Value-at-Risk models in Chernozhukov and Umantsev (2001) and Engle and Manganelli (2004), Adrian and Brunnermeier (2011) studies the tail-dependence of entities, and proposes $\Delta CoVaR$ as a risk measure for systemic risk spillovers. Acharya et al. (2010) extends the concept of expected shortfall to "marginal expected shortfall" (MES) to study the capitalisation needs for a financial institution when the market is in distress and propose a "systemic expected shortfall" SES measure as a composite measure for systemic risk, which is later extended in Brownlees and Engle (2012) with a dynamic estimates of MES.

One of the advantages of market-based systemic measures is that they provide consistent systemic measures. Since the main source of information of market-based measures comes from long-running market risk indicators (from the stock/bond prices and CDS spreads regarding individual institutions to interbank lending rates and market volatility indicators regarding the market), these sources provide standardised and high-frequency risk estimates. Bisias et al. (2011) comments on the ineffectiveness of statement-based measures in providing consistent risk estimates, as on one hand the risk exposures of newly emerged contingent contracts could not be adequately captured by financial reports, on the other hand the supervisors could not access to consistent and regular update of industry information such as sizes of market segments. In addition, differences in accounting and supervisory standards make it difficult to have a cross-border assessment of systemic risk status in different economic regions.

Another advantage of market-based measures is that they allow for the capturing of indirect spillover effects of market contagion as well as assessing the overall systemic risk status of the market. As discussed in Section 2.1.2, the sources from where systemic risk originates not only include the mutual contractual links, but also the indirect spillovers due to mark-to-market asset losses, deterioration of market confidence. Drehmann and Tarashev (2011) shows that, while statement-based measures can provide parsimonious indicators that are good approximations to market-based measures in terms of assessing the systemic importance of individual financial institutions, they could not provide good measures regarding the aggregate systemic risk in the financial market. A common exogenous shock, such as from sovereign credit risk, would simultaneously affect all market participants with similar portfolio and lead to the potential scenario of multiple defaults, which require examining the "bigger-picture" for risk assessment. Therefore, market-based measures can provide assessment of the systemic risk contribution of a financial institution to the entirety of the system, as well as the overall state of systemic risk regarding the market.

Another advantage is that given the high frequency of the indicator series, market-based measures provide timely risk estimates, which enables policy-makers to gain insights into the current stability status of the financial system. In addition, the forward-looking nature of the financial market indicators allow for the development of early warning systems from market-based measures. For example, the CDS spreads contains the average expected default probability during the life of the contract, whereas balance-sheet data provides only backward-looking measures indicating past information rather than "what is expected to happen in the future". As critisised in Adrian and Brunnermeier (2016), contemporaneous measures of systemic risk which relies on volatility as a proxy for risk could the capture the build-up of volatility over the time horizon, since financial institutions take on excessive risk in when the market is in moderate conditions, and therefore extreme market conditions are the consequences of systemic risk, rather than the cause of it. Brownlees and Engle (2012) shows that the $SRISK$ measure of systemic risk is found to granger-cause industrial production, where the authors argue that the risk measure can correctly proxy the capital shortages in the financial market, and the deterioration of which impairs industrial production and the real economy and is successfully depicted in their model.

2.2.2 CDS Spreads as A Systemic Risk Indicator

Mechanism of Credit Default Swaps

A credit default swaps (CDS) contract is a swaps contract on the credit risk of the contingent default (or other "credit events") of the reference entity. In contrast to a bond contract where the investor needs to have risk position on the reference entity's credit risk, a CDS contract between the protection buyer and the protection seller allows their risk positions to be managed independently of the reference entity. Therefore, the CDS on the reference entity serves as an insurance contract which transfer the credit risk of default from the protection buyer to the protection seller in exchange for an annual fee payment (spread). When the reference entity fails to meet its debt obligations, a credit event is triggered and the protection buyer receives from the protection seller an insurance payment equal to the difference between the notional principal and the loss upon default of the underlying reference obligation (Duffie, 1999; Augustin, 2012).

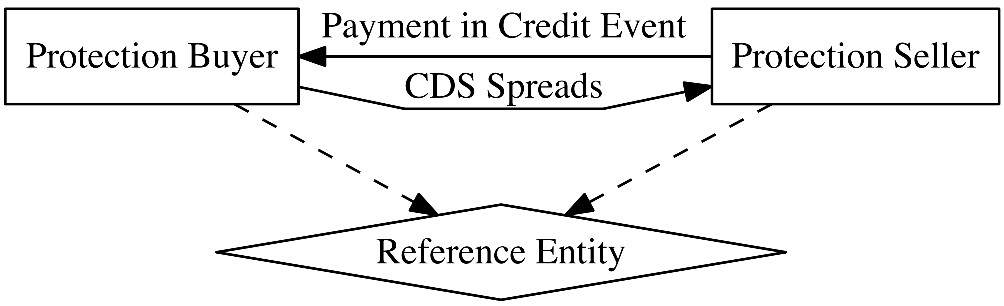

Figure 2.2: Credit Default Swaps Mechanism

Source: Weistroffer et al. (2009)

From the perspective of the protection seller, it is exposed to the risk of default by the reference entity and the contingent payment of the protection contract. Therefore, the major component of the CDS spreads charged by the protection seller should generally reflect the market perception regarding the credit risk of the reference entity, which in turn provides a market indicator of credit risk. In the theoretical pricing models of CDS spreads (Duffie, 1999; Tarashev and Zhu, 2006), the spreads of a T-year CDS contract can be modelled as

$$s_{i,t} = \frac{(1 - R_{i,t}) \int_t^{t+T} e^{-r_\tau \tau} q_{i,\tau} d\tau}{\int_{\tau=t}^{t+T} e^{-r_\tau \tau} \left[1 - \int_{\tau=t}^{\tau} q_{i,u} du\right] d\tau} \tag{2.1}$$

where $R_{i,t}$ is the recovery rate, r_t is the risk-free interest rate, $q_{i,t}$ is the risk-neutral default intensity and $1 - \int_t^\tau q_{i,u} du$ denotes the risk-neutral probability of bank i's survival over the τ years. The one-year risk-neutral probability of default is derived from CDS spreads as:

$$\begin{aligned} PD_{i,t} &= \frac{a_t s_{i,t}}{a_t LGD_{i,t} + b_t s_{i,t}} \\ a_t &= \int_{\tau=t}^{t+T} e^{-r_t \tau} d\tau, b_t = \int_{\tau=t}^{t+T} \tau e^{-r_t \tau} d\tau, \\ LGD_{i,t} &= (1 - R_{i,t}) \end{aligned} \tag{2.2}$$

Therefore, as discussed in Huang et al. (2012*b*), the probability of default implied by the credit risk spreads contains three elements: the compensation (premium) for expected default losses, the compensation for bearing the default risk, and the compensation for bearing other types of risk, such as liquidity risk or uncertainty risk. The increase in CDS spreads can thus be attributed to the increases in the default and liquidity risk premium components. In addition, Lahmann and Kaserer (2011) also demonstrate the effectiveness of CDS spreads in indicating the credit risk level by showing that the spreads are a first-order approximation of the constructed expected systemic shortfall estimates.

Empirical Applications of CDS Spreads

Empirical studies document the effective evidence of CDS spreads as an instrument of credit risk monitoring. As noted by Rodriguez-Moreno and Pena (2012), stock prices data lacks the inherent direct measure of default probability in CDS market and thus it needs specific structural model to provide risk estimates measures, such as the implied credit spread model by Forte (2011). Comparing the indicators of credit risk, the advantage of CDS series over corporate bond rates is its liquidity: CDS series are calculated from standardized CDS contracts which are traded in large volumes, whereas corporate bond markets are segmented and not standardized. As noted by Blanco, Brennan and Marsh (2005), CDS market provides the easiest place where the trading of credit risk can take place without suffering from the various short-sales constraints in the bond market.

In terms of the empirical findings regarding the effectiveness of information in different market series, several studies show that CDS market lead other markets, such as Blanco et al. (2005) for the comparisons between corporate investment-grade bonds and CDS spreads, and Fontana and Scheicher (2010) and Ammer and Cai (2011) for sovereign bond market and sovereign CDS market. In addition, Rodriguez-Moreno and Pena (2012) compares the performance of market-based methods using interbank rates, stock prices, and CDS series. The authors show that risk measures calculated from CDS data outperform others as for macro-prudential measures the first principal component of a portfolio of CDS spreads provides the best estimates whereas for micro-prudential measures multivariate densities of CDS spreads is the best measure.

Therefore, CDS series including financial institutions CDS, sovereign CDS, and

CDS indices has now been widely used in the measuring of systemic risk. The DIP measures of Huang et al. (2012*a*,*b*) rely on CDS spreads to calculate the probability of defaults for financial institutions. Acharya et al. (2010) discuss an implementation of their MES method using CDS data and find that the risk measures can explain more of the tail behaviour of the systemic risk estimates. Wong and Fong (2011) calculates the $\Delta CoVaR$ estimates for Asia-Pasific sovereign economies using their sovereign CDS, and Fong and Wong (2012) $\Delta CoVaR$ is also implemented using CDS data for Asia-Pacific sovereign economies (Wong and Fong, 2011) and European Sovereign economies (Fong and Wong, 2012). Betz, Hautsch, Peltonen and Schienle (2015) proposes a network model regarding the risk spillovers of sovereign and bank CDS series.

2.2.3 Market-based Systemic Risk Measures

Here we discuss the two market-based measures that are mostly adopted[3] in systemic risk measures: $\Delta CoVaR$ by Adrian and Brunnermeier (2011) and Adrian and Brunnermeier (2016), and marginal expected shortfall by Acharya et al. (2010) and Brownlees and Engle (2012).

$\Delta CoVaR$

As a systemic risk measure, $\Delta CoVaR$ calculates the risk spillovers from the "originator" entity to the "receptor" entity, i.e. the contributions of the origin's distress to the distress of the receptor. $\Delta CoVaR$ builds upon the concept of "Conditional Value-at-Risk", which is the receptor's level of distress as quantified by its value-at-risk

[3]Bisias et al. (2011) and Benoit et al. (2016) provide comprehensive surveys on systemic risk and the techniques measuring systemic risk. Among the risk measures in the surveys, $\Delta CoVaR$ and MES are the two methods most cited in Google Scholar. As of 05/November/2016, Adrian and Brunnermeier (2011, 2016) are cited 1398 times, Acharya et al. (2010) 1161 times, and Brownlees and Engle (2012) 506 times.

conditional on the realised event of the originator experiencing a loss as quantified its value-at-risk. The difference of, 1) the receptor's q^{th}-quantile value-at-risk conditional on the originator's q^{th}-quantile value-at-risk, and 2) the receptor's q^{th}-quantile value-at-risk conditional on the originator's median state, thus measures the spillovers of risk transferred from the originator's distress to the receiver. Therefore, the spillovers from one financial institution's distress to the systemic index measures its systemic risk contribution, and a large risk spillovers from an originator institution should therefore prompt actions from regulators to prevent the potential scenario of a systemic event.

Formally, the q^{th}-quantile value-at-risk of a series X of institution i can be expressed as the following, where the quantile q denotes the rarity of the event:

$$Pr(X^i \leq VaR_q^i) = q \tag{2.3}$$

$CoVaR_q^{j|C(X^i)}$ then measures the q^{th}-quantile value-at-risk of institution j conditional on event $C(X^i)$ regarding institution i:

$$Pr(X^j|C(X^i) \leq CoVaR_q^{j|C(X^i)}) = q \tag{2.4}$$

Therefore $\Delta CoVaR_q^{j|i}$ is the difference in j's values-at-risk conditional on two events:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{0.5}^i} \tag{2.5}$$

In a simplified Gaussian case, suppose the structure of returns of institutions i and

j as well as their conditional returns are as follows:

$$(X_t^i, X_t^j) \sim N\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}(\sigma_t^i)^2 & \rho_t\sigma_t^i\sigma_t^j\\ \rho_t\sigma_t^i\sigma_t^j & (\sigma_t^j)^2\end{pmatrix}\right) \tag{2.6}$$

$$X_t^j|X_t^i \sim N\left(\frac{X_i^t\sigma_t^j\rho_t}{\sigma_t^i}, (1-\rho_t^2)(\sigma_t^i)^2\right) \tag{2.7}$$

$CoVaR_{q,p,t}^{j|i}$ the q^{th} VaR of institution j conditional on the p^{th} VaR of institution i, as defined in (2.4), is then as the following, where Φ is the standard Gaussian CDF:

$$Pr\left(\left[\frac{X_t^j - X_t^i\rho_t\sigma_t^j/\sigma_t^i}{\sigma_t^j\sqrt{1-\rho_t^2}}\right] < \left[\frac{CoVaR_{q,p,t}^{j|i} - X_t^i\rho_t\sigma_t^j/\sigma_t^i}{\sigma_t^j\sqrt{1-\rho_t^2}}\right]|X_t^i = VaR_{p,t}^i\right) = q \tag{2.8}$$

$$CoVaR_{q,p,t}^{j|i} = \Phi^{-1}(q)\sigma_t^j\sqrt{1-\rho_t^2} + \Phi^{-1}(p)\rho_t\sigma_t^j \tag{2.9}$$

$\Delta CoVaR_{q,t}^{j|i}$, as defined in (2.5), where we use the same tail rarity q for i and j, is then:

$$\Delta CoVaR_{q,t}^{j|i} = \Phi^{-1}(q)\rho_t\sigma_t^j \tag{2.10}$$

Adrian and Brunnermeier (2011) provide two approaches to estimate $CoVaR$, using quantile regression models of Koenker and Bassett Jr (1978) and using bivariate diagonal vec $GARCH(1,1)$ models, and show that the backtest performance of quantile regression models are better than $GARCH(1,1)$ models. For other extensions, Lopez-Espinosa, Moreno, Rubia and Valderrama (2012) provides a $CoVaR$ quantile model which takes account of the asymmetric information of the tails, Cao (2012) provides a $CoVaR$ estimator based on Sharpley values, and Girardi and Tolga Ergün (2013) use a multivariate $GARCH(1,1)$ model to estimate $CoVaR$.

Marginal Expected Shortfall

Margin expected shortfall is defined as the expected loss in equity of a financial institution when the market declines substantially in a crisis situation. Denote $R_i = \sum_j y_j r_j$ to be the return of an entity i where r_j is the return of the j^{th} group and y_j being j^{th} weight in the portfolio. The expected shortfall ES for the entity can be define as

$$ES_q^i = -\mathbb{E}\left[R_i | R_i \leq -VaR_q^i\right] = -\sum_j y_j \mathbb{E}\left[r_j | R_i \leq -VaR_q^i\right] \tag{2.11}$$

where VaR_q^i is the q^{th}-quantile value-at-risk. In Acharya et al. (2010), the marginal expected shortfall MES^j of group j is then defined as the sensitivity of the entity's overall risk to the exposure y_j in each group j:

$$MES_q^j = \frac{\partial ES_q}{\partial y_j} = -\mathbb{E}\left[r_j | R_i \leq -VaR_q^i\right] \tag{2.12}$$

When we treat the entity as a systemic portfolio, in the context of a systemic events, MES_q^i, the margin expected shortfall for institution i, conditional on the market experiencing its worst q^{th} returns is calculated as:

$$MES_q^i = \mathbb{E}\left[\frac{w_{t=1}^i - w_{t=0}^i}{w_{t=0}^i} | I_q\right] \tag{2.13}$$

where $(w_{t=1}^i - w_{t=0}^i)/w_{t=0}^i$ is the net equity returns of institution i and I_q is the indicator for the market return being in its lower left q^{th} quantile. In Acharya et al. (2010), MES_q^i is estimated as the average stock returns for institution i conditional on market distress

$$MES_q^i = \frac{1}{\#days} \sum R_{i,t} \tag{2.14}$$

Acharya et al. (2010) then defines the systemic risk contribution of institution i as its systemic expected shortfall SES_q^i, which consists of its leverage level as well as its MES:

$$\frac{SES_q^i}{w_0^i} = \frac{za^i - w_0^i}{w_0^i} + kMES_q^i + \Delta^i \tag{2.15}$$

where the term $\frac{za^i - w_0^i}{w_0^i}$ denotes the insitution's leverage level, k is a scale factor, and Δ^i is an adjustment term.

As an extension, Brownlees and Engle (2012) develops a dynamic version of MES which provides multi-step ahead forecast capability as an early warning system.

Denote $R_{i,t}$ and $R_{M,t}$ to be the return of institution i and the return of a market index, and they are assumed to follow the bivariate process:

$$\begin{aligned} R_{M,t} &= \sigma_{M,t}\epsilon_{M,t}^1 \\ R_{i,t} &= \sigma_{i,t}\rho_{i,t}\epsilon_{M,t}^2 + \sigma_{M,t}\sqrt{1-(\rho_{i,t})^2}\epsilon_{i,t}^2 \\ \left(\epsilon_{M,t}^1, \epsilon_{j,t}^2\right) &\sim \mathbf{H} \end{aligned} \tag{2.16}$$

where $\sigma_{M,t}$ and $\sigma_{i,t}$ are the conditional volatilities of the market return and institutions i, and $\rho_{i,t}$ is their conditional correlation. Innovations are introduced into the process via $\left(\epsilon_{M,t}^1, \epsilon_{i,t}^2\right)$, which are assumed to be *i.i.d.* with $\mathbb{E}\left(\epsilon_{j,t}^i\right) = 0$, $Var\left(\epsilon_{j,t}^i = 1\right)$ for $n \in \{1, 2\}$ and $j \in \{i, M\}$ and zero covariance.

The one-period-ahead MES for a systemic event S can be calculated as

$$\begin{aligned} MES_{i,t-1}^1 &= \mathbb{E}_{t-1}\left(R_{i,t}|R_{M,t} < S\right) \\ &= \sigma_{i,t}\mathbb{E}_{t-1}\left(\rho_{i,t}\epsilon_{M,t}^1 + \sqrt{1-(\rho_{i,t})^2}\epsilon_{j,t}^2 | \frac{S}{\sigma_{M,t}}\right) \end{aligned} \tag{2.17}$$

Denote $R_{i,t:t+h-1}^k$ and $R_{M,t:t+h-1}^k$ to be the k^{th} simulated cumulative return of institution i and the market, the h-step ahead dynamic MES can then be estimated as the Monte Carlo average of the simulated path of h-step ahead return forecasts:

$$MES^h_{j,t-1} = \frac{\sum_{k=1}^{K} R^k_{j,t:t+h-1} I(R^k_{M,t:t+h-1} < S)}{\sum_{k=1}^{K} I(R^k_{M,t:t+h-1} < S)} \tag{2.18}$$

2.3 Sovereign Risk as A Source of Systemic Risk

2.3.1 Determinants of Sovereign Risk Spillovers

Several studies show that the market series regarding sovereign credit risk, i.e. sovereign CDS spreads and bond yields, do incorporate the information of the risk of defaults or fiscal distress of the sovereign countries. Arghyrou, Kontonikas et al. (2011) uses a regime switching model to analyse the varying impact of different factor groups to the sovereign bond yields, and finds that when in a crisis regime, country-specific macro-fundamentals have greater influence to the pricing of sovereign debt. This finding regarding the shift in explanatory powers is also supported in Caceres, Guzzo and Segoviano Basurto (2010), where the authors document the shifts of explanatory powers regarding Sovereign CDS from global risk aversion to country-specific economic fundamentals. Aizenman, Hutchison and Jinjarak (2013) carries a study regarding how the fiscal space of sovereign countries influence their sovereign CDS spreads over 60 countries from 2005 to 2010, in which the study finds that the fiscal space proxies such as deficit-to-tax and public debt-to-tax ratios have good explanation powers in explaining sovereign CDS spreads. In terms of the forward-looking nature of market series, Ismailescu and Kazemi (2010) investigates the effect of credit rating events on the CDS spreads of sovereign countries, and the authors find that the CDS spreads of high grade countries respond more strongly to rating upgrades and the spreads of low grade countries respond more strongly to rating downgrades. In addition, they find that CDS spreads have good forward-looking property as the information of negative rating events is anticipated and incorporated into CDS spreads before the rating announcements.

However, to what extent does the sovereign risk spillovers reflect the credit risk of the sovereign countries? As noted in Augustin (2012), there has been a long debate in the literature regarding whether the spillover effects from sovereign risk series such as sovereign bond yields and CDS spreads, are predominantly explained by the country-specific factors, or by the factors representing the global risk environment and the co-movement of markets. Several studies document the roles of global factors in influencing sovereign risk series, as well as the co-movement of market series in lead-lag relationships, which provide mechanism of risk spillovers via risk premium channels and price discovery channels. Pan and Singleton (2008) constructs a theoretical pricing model of the term structure of sovereign CDS spreads, and show that the risk premium component of the spreads can be well explained by global volatility index as well as other financial variables. Longstaff et al. (2011) examines the effects of variable groups of global factors and variable groups of local factors on the components of sovereign CDS spreads, and the study shows that both the CDS spreads and its components are strongly affected by global determinants such as US equity returns, volatility and bond market risk premia. Therefore, sovereign risk is also strongly subjected to spillovers from global risk environment and from other markets, and the channels of which also allow risk spillovers from sovereign risk to financial institutions.

2.3.2 Dynamics of Sovereign Risk Spillovers

There exists several channels of risk transmission between sovereign risk and financial risk. As shown in the theoretical models of Gray et al. (2008), Drechsler et al. (2011), and Merton, Billio, Getmansky, Gray, Lo and Pelizzon (2013), explicit and implicit guarantees of the sovereign countries create several potential linkages from sovereign countries to financial institutions. As financial institutions hold public bonds and general collateral on their balance sheet, a depreciation in value of the government bonds can therefore affect financial institutions through the asset holding channel. Downgrades of sovereign bonds can also adversely affect the funding conditions of financial institutions. The value of the implicit guarantees provided by sovereign countries can be diminished when the fiscal condition of the sovereign countries are under distress. In addition, the presence of high systemic risk in the financial sector creates pressure for recession in the real economy, which in turns strains public finances that are involved in the state guarantees of the financial sector.

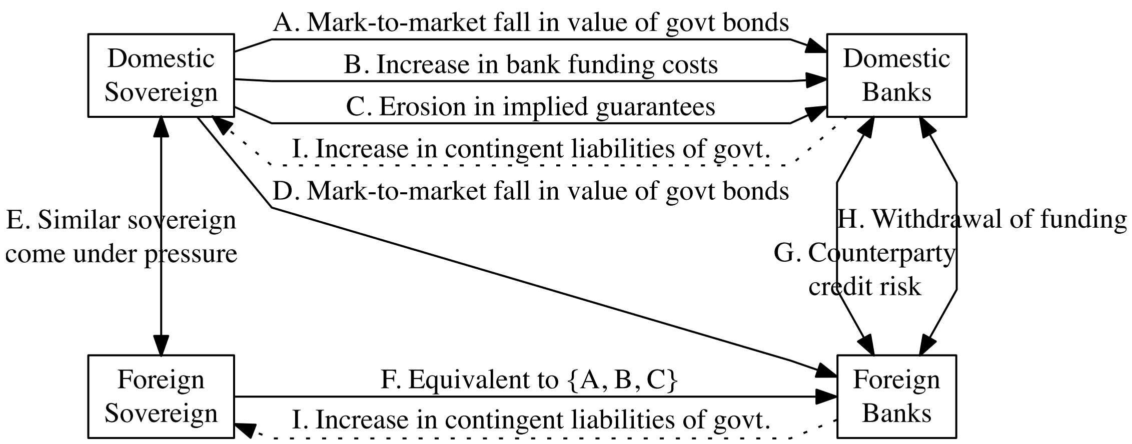

Figure 2.3: Sovereign – Financial Institution Systemic Risk Spllovers

Source: Merton et al. (2013)

Drechsler et al. (2011) documents the two-way feedback effect between sovereign risk and the financial sector: government bailouts negatively impact the fiscal strength of the sovereign, which in turn reduces the value of the government guarantees implicit in the financial institutions and causes collateral damage to the banks' public bond holdings. As a consequence, the CDS spreads of sovereign countries and financial companies co-move strongly once the government has committed excessively to financial guarantees. De Bruyckere et al. (2013) examine the excess correlations of market series for banks and sovereign countries, and they find that there is a stronger relationship of excess correlations between banks and their home country, especially for $GIIPS$ countries. The excess correlation is stronger when the banks are undercapitalised, reliant on wholesale funding, or with higher proportion of non-interest income. Gerlach, Schulz and Wolff (2010) and Dieckmann and Plank (2012) find the evidence of such spillover effects of sovereign debt holding and government contingent liabilities from the linkages of bank and sovereign CDS series. In addition, Demirgüç-Kunt and Huizinga (2010) finds that given the spillover relationships from sovereign countries to financial institutions, the fiscal weakness of sovereign countries can be manifested in the valuation of their domestic financial institutions to be negatively correlated with their size, which instead of making them "too-big-to-fail", the fiscal weakness of sovereign countries make them "too-big-to-save". From the aspects of bilateral linkage spillovers of lead-lag relationships, Alter and Schüler (2012) shows that prior to the financial sector bailout programs, changes in the bank CDS spreads precede changes in the sovereign CDS spreads, whereas after the bailout programs, this lead-lag relationship reverses in general, which suggests the presence of sovereign spillovers. From the perspective of sovereign-to-sovereign spillovers, Bai, Julliard and Yuan (2012) provides a model regarding domestic and aggregate credit and liquidity shocks to economic fundamentals of sovereign countries. They find the shocks to economic fundamentals in the Global Financial Crisis are triggered by liquidity risk while the shocks in the Eurozone Sovereign Crisis are triggered by credit risk. In addition, from the dynamics of shocks they find a "flight-to-liquidity" phenomenon as foreign liquidity shocks have negative impact on the domestic liquidity, and domestic liquidity shocks also have negative impacts on foreign liquidity level.

2.3.3 Measuring Sovereign Risk Spillovers

In terms of the theoretical and empirical frameworks of measuring the systemic risk spillovers from the credit risk of sovereign countries, Drechsler et al. (2011) constructs a theoretical model of interactions among a government, a financial sector and a corporate sector, which models the dynamics of feedback loops between distress of financial institutions and distress of sovereign countries. In a Global Vector-Autoregressive (*GVAR*) model of Pesaran et al. (2004), Alessandri et al. (2009) studies the systemic risk to the UK banking system and the macroeconomy from the perspective of investigating the impact of default cascades of financial institutions. From the perspective of the impact to sovereign distress, Caporale and Girardi (2013) extends the *GVAR* model to study the dynamics of fiscal spillovers to sovereign countries. In addition, in terms of how one market series is affected by another market series, several studies analyse the transmission of information and risk between markets using price discovery analysis and Granger causality analysis (Fontana and Scheicher, 2010; Ammer and Cai, 2011; Palladini and Portes, 2011).

2.4 Network Risk as A Source of Systemic Risk

2.4.1 Systemic Risk in Financial Network

Interconnectedness and Contagion

Network theory and studies on financial networks attempt to address the shortcomings of the traditional approaches from the perspectives of direct pairwise links, indirect interconnectedness, and network structures. Contagion is one of the most important aspect of financial network regarding systemic risk. Studies on financial networks address the dynamics of contagion by examining the interconnectedness of institutions and markets. Although interconnectedness has been widely acknowledged to be an important element of systemic risk, as discussed in Acemoglu et al. (2015), there are conflicting views in earlier literature about the roles of network interconnectedness in systemic risk. On one hand, under the same conditions, a more interconnected financial network could diversify the negative impact to each individual node (Diamond and Dybvig, 1983; Allen and Gale, 2000; Freixas et al., 2000). On the other hand, with the evidence of recent financial crises, interconnectedness is capable of facilitating the propagation of contagion and destabilising the system (Vivier-Lirimont, 2006; Blume, Easley, Kleinberg, Kleinberg and Tardos, 2013). Elliott et al. (2014) discusses the three ingredients of risk cascades, first failures, contagion (second round direct failures), and interconnection (subsequent rounds of stresses), and two aspects of network topology: "integration" (the magnitude of which institutions are exposed to each other) and "diversification" (the extent of which the links are spread out). Different levels of integration and diversification affect the three ingredients differently. Greater integration lowers the likelihood of first failure of an institution as it reduces the dependence on the primitive assets of the institution, where lower integration reduces the probability and extent of contagion.

High diversification mitigates contagion impact on individual institutions as their portfolios become close to market portfolios, as long as the impact of first failures stays below a destabilising threshold. The argument about a critical threshold is also supported by Acemoglu et al. (2015), which also shows that in the presence of a large shock, it would be counterproductive for regulators to try to limit the extent and nature of interbank linkages, whereas providing liquidity injection to the systemically important financial institutions at the times of crisis would help contain the extent of contagion. From an empirical perspective, Mistrulli (2011) also supports that a complete market with high diversification are not always resilient to contagion shocks.

Network-induced Panics

Another aspect of financial networks in systemic risk concerns with the fact that from a contractual perspective, a market player i can only know the direct contract positions with i's counterparties but not the contract positions of i's counterparties with their counterparties. However, these contracts are still indirectly linked back to i. Brunnermeier (2009) discusses this problem of a "network gridlock risk" where market players have no full knowledge about the indirect exposures that they face. It creates extra funding needs or even creates self-fulfilling counterparty credit risk when, without full knowledge of indirect network risk exposures, market participants worry about their risk exposures to counterparties not being fully hedged due to market distress. In a similar way, Freixas et al. (2000) shows that the payment system is also vulnerable to gridlock risk. Babus (2016) discusses the mechanism of market freeze in a network formation game and shows that the presence of frictions causes small exogenous changes to end up with greater effects, which results in all agents withdrawing from the network in equilibrium.

2.4.2 Empirical Applications and Evidence

Country Aggregate Networks

The empirical researches on financial interconnectedness rely on the information regarding the risk positions of nodes as well as the strength of pairwise linkages, the data of which is often available from sector level or country level. The Bank of International Settlements publishes yearly consolidated banking statistics which provides aggregate cross-border holdings of lending/borrowing claims of the banking industry of each country. Elliott et al. (2014) studies the cross holdings of six European countries from the 2011 BIS consolidated data and find that under a scenario of Greece distress, for the GIIPS countries Portugal is the first country to fail when contagion occurs, whereas Italy would be the last of the six EU countries to fall due to its debt holding portfolios are mostly debt of France and Germany. Said (2016) studies On a country aggregate perspective, financial centers like the United States and the United Kingdom form central hubs in the network, and distress of such hubs will result in the collapse of the financial markets in all other countries. For applications of aggregate cross-holdings using other types of data sets, Dehmamy, Buldyrev, Havlin, Stanley and Vodenska (2014) uses the stress test exposure data from European Bank Authority and studies a bipartite networks[4] of financial institutions and assets in the context of Eurozone Sovereign Crisis in 2011, and shows a herding effect where individual nodes select the same set of parameters and behave similarity.

Interbank Cross-Holding Networks

Battiston, Puliga, Kaushik, Tasca and Caldarelli (2012) studies the network of debt holding and equity investment for the top United States banks which received the

[4]A bipartite network is a network system with two distinctive sets of nodes. In the case of Dehmamy et al. (2014), financial institutions constitute one set of nodes, whereas debts of sovereign countries constitute the other set of nodes.

emergency loans programs from 2008 to 2010, which shows that the debt holding relationships of big commercial banks lead to a densely interconnected market where each node is 1-2 steps away. Cont, Moussa and Santos (2013) studies the interbank contagion dynamics using a dedicated dataset about the Brazilian banking system regarding the mutual exposures of interbank participants in six snapshots from 2007 to 2008, where the authors find that systemic risk is concentrated on a few banks and the outcome of contagion is heavily influenced by the heterogeneity of individual banks. Other studies include Martinez-Jaramillo, Pérez, Embriz and Dey (2010) for the Mexican interbank market and Bonaldi, Hortaçsu and Kastl (2015) for the auction bids of participating banks in the main refinancing operations of the European Central Bank. One of the limitations of these studies is that it requires specifically mandated dataset to obtain the particular exposure positions for individual participants, and often restricted to several discrete market snapshots and certain types of exposures, limiting the replicability of their works. As previously documented network effect is not limited to the tangible interbank borrowing/lending relationships, but also through movements in mark-to-market asset prices as well as market confidence by credit risk and liquidity funding risk, and to a wider range of market participants, including broker-dealers and insurance companies.

Reconstructed Networks

Since financial institutions do not disclose their mutual exposures due to confidentiality issues, it is difficult for researchers to obtain the data for institutions' actual pairwise lending and borrowing positions without private and specially mandated datasets, meaning that the actual network structure remains partially known or unknown. However, there are simulation-based approaches which try to "reconstruct" the network structure using partial information such as aggregated positions of institutions, sectors, or countries in the network. The Maximum Entropy method and its variants (Upper and Worms, 2004; Anand, Craig and Von Peter, 2015; Musmeci, Battiston, Caldarelli, Puliga and Gabrielli, 2013), which assumes a dense and fully connected network where co-dependence of nodes are generally homogeneous, generates simulated adjacency matrices under constraints such as aggregate borrowing/lending positions, and reconstruct the underlying adjacency matrix using a matrix that can minimise the divergence distance between the guess matrix and the target matrix. Recent applications using Maximum Entropy method include Mistrulli (2011) with Italian banks, Anand et al. (2015) with Germany banks, and Di Gangi, Lillo and Pirino (2015) with US commercial banks. However, as discussed in Cont et al. (2013) and Roukny (2016) for interbank contractual links, and in Said (2016) for cross-border aggregate markets, exhibits high heterogeneity among nodes, with links not highly sparse for the assumptions of Maximum Entropy method to hold. Hałaj and Kok (2013) also notes that Maximum Entropy methods would underestimate contagion risk when the tail characteristics are not represented due to the model's averaging tail values.

Correlation Networks

Another branch of studies that is more closely linked to the systemic risk measures concerns with the network linkage aspect of market indicators, i.e. the formulation of spillover linkages by market co-movement. Billio, Getmansky, Lo and Pelizzon (2012) studies the such a network formulation of equity market prices revealed by linear and nonlinear Granger Causality Analysis, among institutions in the four major sectors of the US financial market: commercial banks, broker-dealers, insurers, and hedge funds. The study shows that there exists a massive increase in interconnectedness during crisis when individual institutions respond to market distress synchronously, and such increase in interconnectedness further provides good predictive power for the loss of market capitalisation. Billio, Getmansky, Gray, Lo, Merton and Pelizzon (2012) proposes a Contingent Claim Analysis framework to study the network interactions of sovereign countries, commercial banks and insurance companies in the CDS market, in which the network formulation is also conducted by Granger Causality Analysis. Hautsch et al. (2012) and Betz et al. (2015) study the tail dependence network formulated by the co-dependence of value-at-risk series where the value-at-risk network is constructed using a variable selection mechanism based on the "least absolute shrinkage and selection operator" (*LASSO*) method (Tibshirani, 1996). In a similar approach, Demirer, Diebold, Liu and Yilmaz (2015) constructs a globalised banking network of stock returns with a VAR model regularised by the *LASSO* method. In the absence of direct knowledge of bilateral exposures and channels of linkages, statistical pairwise correlation relationships provide valuable indirect information about the network aspects of systemic spillovers. Additionally, given the forwarding looking nature of financial markets, econometric methods provide more immediate and actionable measures of systemic risk.

Chapter 3

Systemic Risk Spillovers – Evidence from CDS Market

3.1 Introduction

The past decade has witnessed a massive surge in the turbulence of the global financial system, triggered by a series of financial and economic crises, e.g. the Subprime Mortgage Crisis, the Global Financial Crisis, and the Eurozone Sovereign Crisis. Extensive research on defining, measuring and regulating systemic risk from financial institutions and sovereign countries has been undertaken since then. One aspect of the studies on systemic risk is the risk spillover effects, as empirical evidence shows that both financial distresses in financial institutions and sovereign credit risk can transcend national borders rapidly, reflecting an extremely high degree of interconnectedness among financial institutions as well as sovereign countries within a larger system.

Policy-makers and regulators are working on identifying the financial institutions that could contribute the most to the overall risk of the financial system that can impose great threat to the safe-and sound-running of the financial system. These institutions can be "too-big-to-fail" or "too-interconnected-to-fail" when they are under distress, so policy-makers are also designing a new regulatory framework for these institutions to ensure global financial stability and to prevent, or mitigate, future episodes of systemic risk spillovers.

In this study, we focus on a particular aspect of the systemic risk of the financial market – the systemic risk spillover effects from sovereign countries to the financial institutions, in the context of the Global Financial Crisis and the Eurozone Sovereign Crisis. The primary interest of our research is to investigate the interlinkage between the sovereign countries and the major financial institutions (including insurance companies and banks) in the financial system, specifically the systemic risk spillover effects and the measure of their interconnectedness.

Our research strategy is two-fold. In the first stage, we construct risk measures of systemic risk spillovers in a system comprised by sovereign countries as well as financial institutions and examine the spillover patterns of our risk measure. We then investigate the potential determinants of risk spillovers from the credit risk of sovereign countries to the financial institutions. We use "Conditional Value-at-Risk" to measure the risk dependencies and spillovers which is proposed by Adrian and Brunnermeier (2011, 2016) in their studies of the systemic risk spillovers among bank holding companies in the United States, and we extend this methodology to the study of spillovers between sovereign countries and financial institutions.

We define the risk of default of an entity in the system as the entity's own "credit risk", and the risk of influencing other entities to default as the entity's "systemic risk". Specifically, the entity i's "systemic risk spillovers" to entity j are constructed as the Conditional Value-at-Risk of j from the median state of the risk of i to the distressed state of i, which is measured as $\Delta CoVaR^{j|i}$. We then construct *CoRisk* as the measure for the "overall systemic contributions" of i as the weighted sum of all the risk spillovers from i to all js.

In order to measure the idiosyncratic credit risk of both the sovereign countries and financial institutions, we use credit default swaps series as the main subjects of our study. Specifically, we construct $\Delta CoVaR^{receptor|originator}$ as the measure of the marginal risk spillovers from an "originator" entity to a "receptor" entity. In our study, $\Delta CoVaR^{FI|SOV}$ measures marginal systemic risk contributions of a sovereign country to a financial institution. We first construct our risk measures for sovereign countries and financial institutions with quantile regression of Koenker (2005) and has been applied to constructing value-at-risk type of measures pioneered by Engle and Manganelli (2004) followed by Adrian and Brunnermeier (2011) and others.

We contribute to the literature in the following ways:

Firstly, previous studies on the sovereign and financial CDS market focus on the risk components and determinants of spreads, as in Pan and Singleton (2008); Longstaff et al. (2011), or the interactions between the bond market and the CDS market, as in Ammer and Cai (2011); Palladini and Portes (2011). We address the problem of distinguishing the default risk of market entities and the spillovers of default risk with the $\Delta CoVaR$ framework, which models the risk spillovers from the tail distributions of market series. We extend the $\Delta CoVaR$ approach to the studies of CDS spreads, in order to understand the effects of risk spillovers from sovereign CDS market to the financial CDS market.

Secondly, we investigate the influence of state intervention measures in influencing the risk spillover dynamics from sovereign countries to financial institutions. The impact of the distress financial institutions to the sovereign countries by the intervention channels is briefly discussed in the studies of De Bruyckere et al. (2013), and our analysis on the sovereign-to-corporate path complements De Bruyckere et al. (2013)

in understanding the consequences of state intervention measures in the Eurozone Sovereign Crisis.

Thirdly, we contribute to the $CoVaR$ literature that is one of the key analytical framework in systemic risk analysis by examining the structural stability of the quantile-based $CoVaR$ risk measures from the quantile structural stability test of Qu (2008) and Oka and Qu (2011).

The rest of the sections are organised as follows. In Section 3.2 we discuss the related literature and our contributions. In Section 3.3 we discuss the methodology framework used to construct systemic risk spillover measures and estimation strategy. In Section 3.4, we report the sources of data and construction of variables. In Section 3.5, we discuss the results related to the construction of the systemic risk measures. In Section 3.7, we examined the potential determinants of the sovereign countries' systemic risk contributions. In Section 3.8, as a robustness check, we discuss the structural stability of the risk measures. In Section 3.9 we discuss the conclusions of this study and offer policy implications.

3.2 Related Literature

Our study relates to the literature of measuring systemic risk using market-based information. The risk spillovers measure of $\Delta CoVaR$ by Adrian and Brunnermeier (2011, 2016) has inspired a series of studies regarding the systemic risk contribution of financial institutions and their exposures to systemic risk. Sharifova (2012) studies the cross-border spillover effects of US and European banks by their equity returns and shows that the firm-specific characteristics such as asset size and leverage level to have positive impacts on the risk spillovers. Lopez-Espinosa et al. (2012) and López-Espinosa, Rubia, Valderrama and Antón (2013) examine the risk contributions of major financial institutions and find that the institution's reliance on short-term wholesale funding plays an important role in determining its systemic risk contributions. Weiß and Mühlnickel (2014) studies the systemic contributions and exposures of insurance companies and find that an insurer's exposures to systemic risk can be largely explained by its reliance on investment income and non-policyholder liabilities, and the insurer's size is found to be the major factor in determining its systemic contributions. Brunnermeier, Dong and Palia (2012) studies the impact of non-interest income of the banks to their contributions of systemic risk and find banks with higher non-interest income and rely on non-interest operations contribute more systemic risk than other banks, and among the different categories of non-interest income, investment banking income and trading income contribute most to the bank's systemic risk. We contribute to this strand of literature by analysing the systemic risk exposure of financial institutions from the perspective of spillovers from sovereign risk.

In addition, our study relates to the theoretical and empirical studies of quantile regression models. Koenker and Bassett Jr (1978) lays the theoretical framework and statistical properties of quantile regression techniques, and Chernozhukov (2005) extends the statistical properties of quantile models to extreme quantiles. Chernozhukov and Umantsev (2001) and Chernozhukov and Du (2006) provide theoretical background of Conditional Value-at-Risk techniques using quantile models. Kupiec (1995), Christoffersen, Hahn and Inoue (2001), and Christoffersen and Pelletier (2004) provide the backtesting techniques for value-at-risk models, and Engle and Manganelli (2004) provides the value-at-risk backtest for quantile models. Engle and Manganelli (2004) also proposes a dynamic quantile-based value-at-risk method, which is extended to the case of conditional value at risk by White, Kim and Manganelli (2015). Qu (2008) and Oka and Qu (2011) apply the structural change test of Bai and Perron (1998) to quantile regression models, and its effect in detecting the locations of breaks and the impacts on regression coefficients have been documented in Oka and Qu (2011) with the time series models for US real GDP growth rate and in Furno and Vistocco (2013) with the panel quantile models of OECD-PISA student tests. We contribute to the literature of quantile regression models by examining the structural stability of the quantile-based $\Delta CoVaR$ risk measures.

Lastly, our study also relates to the studies on CDS market and risk spillovers. Duffie (1999) provide the theoretical pricing model for CDS spreads, how the credit risk of the underlying entity can be measured by its CDS spreads. Duffie et al. (2003) then expands the theoretical model to the case of sovereign CDS spreads and Longstaff et al. (2011) provide the empirical evidence about the effects of macro-financial factors on different components of sovereign CDS. Chan-Lau and Gregoriou (2008) and Chan-Lau (2010) propose a systemic risk measure *CoRisk* with CDS spreads as a proxy for the probability of defaults, and is estimated using a quantile regression model setting, which is later generalised in Adrian and Brunnermeier (2011) and is also implemented in our study. Huang et al. (2012*b*,*a*) propose a distress insurance premium where the probability of default is also estimated from the CDS spreads of financial institutions. There are other studies whose measures of the probability of default are constructed in composite ways such as Forte (2011) and Merton et al. (2013) also rely on CDS information to supplement other indicators, such as stock prices or balance-sheet information. Based on the theoretical and methodological frameworks of previous studies, we contribute to the analysis of systemic defaults in the CDS market by providing evidence of risk spillovers from sovereign CDS series to financial CDS series. In addition, we provide evidence on how the economic fundamentals and government interventions in financial markets are reflected in the market-based risk spillovers information.

3.3 Methodology

3.3.1 $\Delta CoVaR$ as a measure for risk spillovers

$\Delta CoVaR$ by Adrian and Brunnermeier (2011) and Adrian and Brunnermeier (2016) provides a way of measuring the risk spillovers between two series[1]. In the context of our study, denote s_t^i as the CDS spreads of an entity (financial institution or sovereign country) i, thus an unusually high s_t^i suggests a high probability of default for i, which can be represented by the value-at-risk VaR_q^i at the q^{th}-quantile.

$$\Pr(s_t^i \geq VaR_q^i) = q \tag{3.1}$$

In contrast to the VaR of asset returns, where the lower tail of asset returns are the quantiles of interest, we are interested in the upper tail (95% or 99%) of CDS spread, i.e. the probability of default given an event of $(1-q)$ rarity. We can then use "Conditional Value-at-Risk" or $CoVaR$, from Adrian and Brunnermeier (2011), to represent the distress scenario of entity j conditional on the event of entity i's distress.

$$\Pr(s_t^j \geq CoVaR_q^{j|i} \mid s_t^i = VaR_q^i) = q \tag{3.2}$$

$\Delta CoVaR_q^{j|i}$, the difference between the $CoVaR$ conditional on VaR_q^i and the $CoVaR$ conditional on the median state of i, then measures the increment in $CoVaR_q^{j|i}$ when i moves from its median state to its value-at-risk state. In our case $\Delta CoVaR_q^{j|i}$ is the component of the increases in j's risk level induced by i's shift of state:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|r_t^i = VaR_t^i} - CoVaR_q^{j|r_t^i = Median_t^i} \tag{3.3}$$

[1] We discuss the concept behind $\Delta CoVaR$ in Section 2.2.3.

Therefore in the context of our study, we use $\Delta CoVaR_q^{j|i}$ as the measure of spillovers of risk from the distress of country i to financial institution j.

3.3.2 Estimation of Time-varying $\Delta CoVaR$

Quantile Regression Modelling of $CoVaR$

In a linear quantile model setting, we assume the returns for institution j have a linear factor structure as the following, where s_j and s_i are the CDS spreads of j and i, $\mathbf{M}_t$ is the vector of conditioning state variables, and ΔZ_{t+1}^j is the $N(0,1)$ disturbance term:

$$s_{t+1}^j = \phi_0 + \mathbf{M}_t\phi_1 + s_{t+1}^i\phi_2 + (\phi_3 + \mathbf{M}_t\phi_4)\Delta Z_{t+1}^j \tag{3.4}$$

From the definition of value-at-risk, $CoVaR_q^{j|i}$ can then be expressed as the inverse CDF of s_{t+1}^j conditional on the specific state of s_{t+1}^i:

$$CoVaR_{q,t+1}^{j|i} = F_{s_{t+1}^j}^{-1}(q|Mt, s_{t+1}^i = VaR_{q,t+1}^i) \tag{3.5}$$

$$F_{s_{t+1}^j}^{-1}(q|Mt, s_{t+1}^i) = (\phi_0 + \phi_3 F_{\Delta Z^j}(q)) + \mathbf{M}_t\left(\phi_1 + \phi_4 F_{\Delta Z^j}^{-1}(q)\right) + \phi_2 \tag{3.6}$$

$$= \alpha_q + \mathbf{M}_t\gamma_q + s_{t+1}^i\beta_q \tag{3.7}$$

We can then use quantile regression model of Koenker and Bassett Jr (1978) to solve for the q-th quantile fit:

$$\min_{\alpha_q,\beta_q,\gamma_q} \Sigma_t \begin{cases} q\left|s_{t+1}^j - \alpha_q - \mathbf{M_t}\gamma_q - s_{t+1}^i\beta_q\right| & when\left(s_{t+1}^j - \alpha_q - \mathbf{M_t}\gamma_q - s_{t+1}^i\beta_q\right) \geq 0 \\ (1-q)\left|s_{t+1}^j - \alpha_q - \mathbf{M_t}\gamma_q - s_{t+1}^i\beta_q\right| & when\left(s_{t+1}^j - \alpha_q - \mathbf{M_t}\gamma_q - s_{t+1}^i\beta_q\right) < 0 \end{cases} \tag{3.8}$$

Estimation Strategy

We estimate $CoVaR$ using quantile regressions which provides time-varying measures of VaR and $CoVaR$. The basic estimation strategy is implemented as follows: 1) we first estimate the VaRs for a pair of "originator"(an entity that is potentially causing systemic risk spillovers) and "receptor"(an entity that is likely to receive the spillovers from "originator") from their CDS series respectively; 2) we than estimate the $CoVaR$ for the "receptor" conditional on the VaR of the "originator"; 3) the $\Delta CoVaR$ for the "receptor | originator" pair will then be calculated; 4) after calculating $\Delta CoVaR$ for each pair of "receptor | originator" in the sample[2], we calculate the weighted sum of all the sovereign "originators" to measure the overall systemic spillovers from one sovereign country to all financial institutions in the sample.

Specifically, for a "originator" entity in a "receptor | originator" pair, we estimate the following equation using quantile regression estimation, where s_t^j is the CDS spread for institution j. In the following text, we denote the "receptor | originator" pair as a $j|i$ pair to keep the notation concise.

$$s_t^i = \alpha_q^i + \gamma_q^i M_{t-1}^i + \epsilon_t \tag{3.9}$$

where s_t^i is the CDS spreads for the i entity, M_{t-1} is the set of lagged state variables (discussed in Section 3.4). The coefficients $\hat{\alpha}_q^i$ and $\hat{\gamma}_q^i$ are obtained under a specific quantile(here $q = 0.95$)[3]. $VaR_{q,t}^i$ is then calculated from the fitted values as:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}^i \tag{3.10}$$

[2]a "originator" in one pair can be the "receptor" in another, as well as the "receptor" where the "originator" is the "receptor" in the first pair

[3]We are interested in the upper quantiles of the CDS spreads, because an increase in the CDS spreads indicates a worsening of the credit risk of the entity which is also likely to cause risk spillovers. In the literature where asset returns are used to estimate the VaRs and $CoVaR$s the downside risks are considered.

For a $j|i$ pair, we then estimate the CDS spreads for the j entity with the set of state variables M_{t-1} and also the CDS spreads for the i entity:

$$s_t^j = \alpha_q^{j|i} + \beta_q^{j|i} s_t^i + \gamma_q^{j|i} M_{t-1}^j + \epsilon_t \tag{3.11}$$

We obtain $\hat{\alpha}_q^{j|i}$, $\hat{\beta}_q^{j|i}$ and $\hat{\gamma}_q^{j|i}$ from estimating the equation above, and calculate $CoVaR_{q,t}^{j|i}$ in the following way:

$$CoVaR_{q,t}^{j|i} = \hat{\alpha}_q^{j|i} + \hat{\beta}^{j|i} VaR_{q,t}^i + \hat{\gamma}_q^{j|i} M_{t-1}^{j|i} \tag{3.12}$$

As the measure of the marginal increase in the Conditional Value-at-Risk for j entity, we calculate $\Delta CoVaR_{q,t}^{j|i}$ as the difference between $CoVaR_{q,t}^{j|s_t^i=VaR_{q,t}^i}$ and $CoVaR_{q,t}^{j|s_t^i=VaR_{0.5,t}^i}$:

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{j|i} - CoVaR_{0.5,t}^{j|i} \tag{3.13}$$

In the last step, in order to understand the systemic risk spillovers from sovereign countries to financial institutions, following the approach in Chan-Lau (2010), we construct an indicator measuring the systemic risk contributions for the sovereign countries that are identified as "originators" in the system.

$$CoRisk_t^i = \sum_{j=1}^{n} \omega_{j,t} \Delta CoVaR_{q,t}^{j|i},\ \omega_{j,t} = W_t^j (\sum_{j=1}^{n} W_t^j)^{-1} \tag{3.14}$$

We use the total assets of the j financial institutions as the weights in the equation above.

3.4 Data and Variables

3.4.1 CDS Data

We included 30 sovereign countries and 49 financial institutions in our study sample. The Thomson Reuters CDS database from Datastream contains both the sovereign and corporate credit default swaps data from December 2007. The sovereign countries included in our studies contain: 1) countries that are considered as European "core" countries in the Eurozone (Germany, France, Austria, Belgium, the Netherlands); 2) countries that are considered as "distress" sometimes during the Eurozone Sovereign Crises (Cyprus, Greece[4], Ireland, Italy, Portugal, Spain); 3) other member states in the European Union or in the Scandinavian region (Denmark, Sweden, Norway, Finland, Iceland, Bulgaria, Croatia, Czech Republic, Latvia, Estonia, Hungary, Lithuania, Poland, Slovakia, Slovenia); and 4) other major financial centres in the world economies (US, UK, Japan, China). We focus on the first two groups of countries while using the last two groups as comparisons. The financial institutions included in our study consists of the institutions that are defined as the "Systemically Important Financial Institutions" by the Financial Stability Board (FSB), including insurance companies and banks/bank holding companies (Financial Stability Board, 2013*a*,*b*). We also expand this set of institutions with a set of banks that are included in the study of Lopez-Espinosa et al. (2012).

[4]the sovereign CDS for Greece discontinued in early 2012 after a dramatic climb in the series which concluded in a "credit event" that the sovereign debt restructuring of the Greek government bond by the EU and IMF and the repayment to the protection buyers. To construct a continuous series for the Greek sovereign CDS, we follow the approach of Buchholz and Tonzer (2013) to splice it with the CDS for the National Bank of Greece.

3.4.2 State Variables

For the state variables to be included in the first stage construction of risk measures, we collect variables that reflects the movement in the financial markets in order to account for the fluctuations of the CDS series. The state variables represent factors in the financial markets that influence the movement of the credit default spread series. The choice of state variables are widely adopted in the previous studies regarding other market-based systemic risk measures (Chan-Lau and Gregoriou (2008), and Huang et al. (2012*a*)) and specifically measures involving *CoVaR* methodology (Adrian and Brunnermeier (2011), Lopez-Espinosa et al. (2012) and Girardi and Tolga Ergün (2013)[5]), and has been applied to the studies of sovereign credit default swaps (Fong and Wong (2012),Pan and Singleton (2008), and Heinz and Sun (2014)). For descriptive statistics of the state variables, see Table 3.1.

The state variables are divided into 7 categories:

1. Financial Market Volatility, proxied by stock market volatility indices:
   (a) VIX (`sv_vix`): volatility index for S&P500 index
   (b) VDAX (`sv_vdax`): volatility index for DAX index
2. Financial Market Liquidity, proxied by the difference between 3m repo rate and 3m bond rate:
   (a) Liquidity in US Market (`sv_liq_us`)
   (b) Liquidity in Europe Market (`sv_liq_eu`)
3. Changes in the short-term government bond yield spread:

[5] in Girardi and Tolga Ergün (2013), the authors' primary analysis is done using Multivariate GARCH to construct *CoVaR* and they also use Adrian and Brunnermeier (2011)'s choice of state variables for comparisons.

(a) Changes in the 3 month US government bill rate (`sv_d3m_us`)

(b) Changes in the 3 month weighted Eurozone government bond yield spread (`sv_d3m_eu`), obtained from the European Central Bank

4. Term Premium, proxied by the changes in the slope of the yield curve, measured as the yield spread between 10 year bond rate and 3 month bond rate:

   (a) Term Premium of the US government bond (`sv_trm_us`)

   (b) Term Premium of the Eurozone government bond (`sv_trm_eu`)

5. Financial Market Credit Risk Premium (`sv_crt`), measured as the spread between Moody's BAA corporate index and 10yr US government bond

6. Financial market return

   (a) Financial market return of the US market (`sv_mkt_us`), proxied by the return of the S & P 500 index

   (b) Financial market return of the EU market (`sv_mkt_eu`), proxied by the return of the FTSEEU100 index

7. Volatility of the currency (`sv_cv_gbp`, `sv_cv_eur`, `sv_cv_cny`, `sv_cv_jpy`), measured as the Implied volatility for the currency options

Table 3.1: **Descriptive Statistics for State Variables**
Table 3.1 reports the descriptive statistics for the state variables to be included in the quantile regression estimation of *VaR* and *CoVaR*. The constructed variables of risk measures starts from January 2008 to October 2014 in weekly frequency. For the definition of the variables see discussions in Section 3.4.

Variable	Mean	Std. Dev.	Obs.
sv_l_vix	23.82	10.76	312
sv_l_vdax	25.78	10.21	312
sv_l_liq_us	0.19	0.16	312
sv_l_liq_eu	0.07	0.09	312
sv_l_d3m_us	-0.01	0.03	312
sv_l_d3m_eu	0.00	0.02	312
sv_l_trm_us	2.51	0.69	312
sv_l_trm_eu	2.16	0.88	312
sv_l_crt	3.25	0.83	312
sv_l_mkt_us	0.27	0.38	312
sv_l_mkt_eu	0.84	0.58	312
sv_l_cv_gbp	10.77	3.65	312
sv_l_cv_eur	11.85	3.29	312
sv_l_cv_cny	2.72	1.35	312
sv_l_cv_jpy	11.93	2.81	312

3.4.3 Macroeconomic and State Intervention Variables

In the second stage of our analysis, we investigate the determinants of the systemic risk contributions of the sovereign countries during the Global Financial Crisis and Eurozone Sovereign Crisis. Specifically, we examine two categories of variables: the sovereign countries' macroeconomic characteristics(including the debt to GDP ratio, fiscal surplus/deficit to GDP ratio, GDP growth rate), and the European countries' intervention schemes to "bail out" troubled financial institutions. The data for state intervention schemes is reported by European Commission and fall into four categories: guarantee on liabilities, recapitalisation, direct short term liquidity support, and asset relief measures.

The guarantee on liabilities is a public support against the potential losses of the newly issued or renewed debt instruments(excluding subordinated debt) of the financial institutions which help restore the financial stability and provision of credit and lending to the real economy by alleviating the fire sales and liquidity constraints in times of distress. The recapitalisation schemes include capital injections from a national scheme or an *ad hoc* with the acquisitions of stakes by the fiscal authority. Asset relief measures aim at relieving the toxic or impaired assets of the financial institutions in the form of purchasing the assets or offering guarantee against the losses of the assets. Direct short term liquidity support refer to the measures to provide direct liquidity to financial institutions.

3.4.4 Data frequencies and Sample period

In terms of data frequencies, in the first stage of our analysis, the credit default swaps data are collected in daily frequencies and converted to weekly frequencies. For other data that are not available in weekly frequencies we use spline interpolation technique to create continuous series. In the second stage where our regression consists of the *CoRisk* measures and macroeconomic characteristics, we collapse the *CoRisk* and sovereign CDS data to quarterly frequency in order to be compatible with the macroeconomic variables that are in lower frequencies.

For the estimation of risk measures, our sample starts from January 2008 to October 2014 with 312 weekly observations.

3.5 Estimation Results

In the first stage of our analysis, we construct the risk measures discussed in Section 3.3. Then we discussed the estimation results and the relative characteristics of these risk measures.

3.5.1 Quantile Model Fit

Firstly, we report the summarised results on the using quantile regression estimation for fitting VaR and $CoVaR$ in Table 3.2 of all the equations. For the 79 VaR models (with respect to each entity) and 6162 $CoVaR$ models (with respect to each receptor-originator pair), we report the median values of fitted coefficients, the standard errors (using Huber Sandwich Heteroskedasticity-consistent estimators), as well as the pseudo-R^2 goodness-of-fit of these models. As discussed in Adrian and Brunnermeier (2016) and earlier in Chernozhukov and Umantsev (2001), the state variables are included in the quantile models as conditioning variables to control for the mean and volatility of the risk measures, and different entities are exposed to these factors in different ways. Therefore the median values can only summarise the entities' general exposures to state variables.

We divide the statistics into SOV group for sovereign countries and FI group for financial institutions. As in Adrian and Brunnermeier (2016), we find factors regarding market volatility, liquidity risk and changes in short term government bond rates to have positive impact on the risk measures. The risk measures of financial institutions are more exposed to changes in the US bond rate whereas the measures for sovereign countries are more exposed to the EU bond rate. In addition, the levels of pseudo-R^2 of the fitted models in our model specifications are consistent with those reported in Adrian and Brunnermeier (2016, p.1721).

Table 3.2: **Summary For Quantile Fit::** VaR **and** $CoVaR$.
Table 3.2 reports the regression fit summary for VaR and $CoVaR$. Values are reported in median values of all estimated equations. The columns for $VaR/CoVaR$ report the median of coefficient values and t-statistics of all estimated equations, and the columns for $VaR^{SOV}/CoVaR^{SOV}$ and $VaR^{FI}/CoVaR^{FI}$ report equations where the receptor entity is a sovereign country/financial institution respectivelly.

Variable	VaR	VaR^{SOV}	VaR^{FI}	$CoVaR$	$CoVaR^{SOV}$	$CoVaR^{FI}$
constant	-8.63	-16.51	4.12	-5.05	-14.70	10.95
	(-0.19)	(-0.64)	(0.09)	(-0.13)	(-0.52)	(0.20)
`spillover`				0.34	0.25	0.45
				(3.19)	(2.99)	(3.20)
`sv_l_vix`	0.92	0.21	1.16	0.47	0.06	0.81
	(-1.87)	(-1.83)	(-1.84)	(-2.06)	(-2.16)	(-1.42)
`sv_l_vdax`	1.28	0.67	1.64	0.87	0.48	1.21
	(2.47)	(2.00)	(2.92)	(1.95)	(1.38)	(2.37)
`sv_l_liq_us`	1.82	2.76	3.85	2.89	3.04	0.46
	(2.13)	(1.41)	(2.18)	(1.23)	(1.36)	(1.03)
`sv_l_liq_eu`	12.20	6.39	19.73	4.32	3.85	9.43
	(2.42)	(2.37)	(2.54)	(2.25)	(2.19)	(2.34)
`sv_l_d3m_us`	62.60	1.94	128.78	28.70	7.22	95.18
	(-1.82)	(-1.19)	(-2.16)	(-1.56)	(1.22)	(-2.43)
`sv_l_d3m_eu`	61.12	111.16	11.19	45.74	65.69	13.66
	(-1.83)	(-1.19)	(-1.81)	(-1.63)	(-1.97)	(-1.18)
`sv_l_trm_us`	-2.27	-2.18	-4.63	-1.25	-1.06	-2.61
	(-1.89)	(-1.92)	(-1.47)	(-1.51)	(-1.48)	(-1.90)
`sv_l_trm_eu`	-0.87	1.16	-2.70	0.35	1.05	-0.36
	(-0.21)	(0.48)	(-0.58)	(0.09)	(0.38)	(-0.11)
`sv_l_crt`	-2.18	-0.52	-5.67	-0.97	-0.16	-1.09
	(-0.56)	(-0.27)	(-1.29)	(-0.26)	(-0.04)	(-0.30)
`sv_l_mkt_us`	0.00	0.01	0.00	0.00	0.01	-0.00
	(0.23)	(0.68)	(0.21)	(0.16)	(0.74)	(-0.08)
`sv_l_mkt_eu`	-0.00	-0.00	-0.01	-0.00	-0.00	-0.01
	(-0.14)	(-0.38)	(-0.35)	(-0.16)	(-0.21)	(-0.32)
`sv_l_cv_gbp`	-0.20	-0.09	-0.05	-0.24	0.06	-0.16
	(-0.19)	(-0.03)	(-0.05)	(-0.21)	(0.05)	(-0.11)
`sv_l_cv_eur`	0.98	1.26	0.59	0.61	0.68	-0.01
	(0.91)	(1.03)	(0.56)	(0.59)	(0.83)	(-0.01)
`sv_l_cv_cny`	0.85	0.05	0.83	0.74	0.03	1.39
	(0.53)	(0.01)	(0.52)	(0.44)	(0.02)	(0.66)
`sv_l_cv_jpy`	0.12	-0.19	0.31	0.06	-0.19	0.26
	(0.22)	(-0.50)	(0.47)	(0.08)	(-0.36)	(0.32)
Pseudo R^2	0.38	0.41	0.37	0.45	0.46	0.46

3.5.2 Likelihood-ratio Tests

In order to further assess the specifications of state variables, In table 3.3 we report the proportions of models where the p-values of which are below the respective levels of significance in likelihood-ratio tests. For each of the state variables, we use a likelihood-ratio test to compare the goodness-of-fit of the unconstrained model using full state variable specifications with a nested model where the specified variable is removed. We report the proportions of models that reject the null hypothesis of indifference between the two models, thus a high proportion suggests the significance of the variable in the model fit and justify its presence in the model specifications. Overall we find most of the variables have good explanatory powers, among which the volatility measures have the greatest effect in the model specifications.

Table 3.3: **Summary of Likelihood Ratio Tests for Quantile Regression Models**
Table 3.3 reports the proportion of likelihood ratio tests that are under the specified level of significance. The test is conducted between the full unrestricted model and the nested restricted model with the specified variable removed. The test null hypothesis states indifference in goodness-of-fit between the two models. The rejection of the null then suggests the removal of the specified variable has significant effect on the model fit.

Variable	*VaR*			*CoVaR*		
	≤ 0.10	≤ 0.05	≤ 0.01	≤ 0.10	≤ 0.05	≤ 0.01
`sv_l_vix`	0.7692	0.6795	0.5897	0.7058	0.6382	0.5168
`sv_l_vdax`	0.9103	0.8974	0.8462	0.8125	0.7712	0.6963
`sv_l_liq_us`	0.4359	0.3974	0.3077	0.4985	0.4199	0.2809
`sv_l_liq_eu`	0.3205	0.2436	0.1282	0.4331	0.3332	0.2053
`sv_l_d3m_us`	0.5897	0.5385	0.4103	0.5871	0.5098	0.3751
`sv_l_d3m_eu`	0.5897	0.5385	0.3590	0.5513	0.4822	0.3535
`sv_l_trm_us`	0.6410	0.6282	0.4615	0.6029	0.5251	0.3958
`sv_l_trm_eu`	0.4231	0.3205	0.2051	0.4557	0.3615	0.2274
`sv_l_crt`	0.6923	0.6410	0.4872	0.6414	0.5808	0.4564
`sv_l_mkt_us`	0.5000	0.4359	0.2949	0.5538	0.4740	0.3283
`sv_l_mkt_eu`	0.3462	0.2692	0.2308	0.4560	0.3691	0.2431
`sv_l_cv_gbp`	0.5385	0.4231	0.2821	0.5543	0.4764	0.3355
`sv_l_cv_eur`	0.6154	0.4744	0.3846	0.6099	0.5373	0.4224
`sv_l_cv_cny`	0.4487	0.3718	0.2949	0.4978	0.4098	0.2822
`sv_l_cv_jpy`	0.5128	0.4231	0.3333	0.4752	0.3828	0.2572
No. models	79			6162		

3.6 Credit Risk and Systemic Risk Spillovers

3.6.1 VaR, $CoVaR$, and $\Delta CoVaR$

As discussed in previous Section 2.2.2 and Section 3.3, the VaR of the entity's CDS spreads measures the credit risk level of the underlying sovereign/corporate bond, whereas $CoVaR^{j|i}$ adjusts entity j's value-at-risk conditioning on i's value-at-risk. $\Delta CoVaR^{j|i}$ then measures the increments in $CoVaR^{j|i}$ with the shifting in the conditioning event.

Table 3.4: **Descriptive Statistics Of Fitted Variables**.
Table 3.4 reports the descriptive statistics of the risk measures using quantile regression. The construction method is described in Section 3.3

Variable	Mean	Std.Dev.	Obs.
VaR	24.35	34.01	24,336
$CoVaR$	30.41	38.19	1,873,872
$CoVaR^{SOV}$	28.25	33.47	696,696
$CoVaR^{FI}$	31.69	40.66	1,177,176
$\Delta CoVaR$	7.97	10.62	1,873,872
$\Delta CoVaR^{SOV}$	8.70	11.16	696,696
$\Delta CoVaR^{FI}$	6.73	9.52	1,177,176

Table 3.4 reports the descriptive statistics for the respective estimated risk measures. In our sample, we observe that on average the 0.95^{th}-quantile VaR for CDS spreads in 24.35 basis points[6]. When accounting for the event of the distress of the "originator", the $CoVaR$ of a "receptor" is higher than its VaR. Lastly, we observe that the average risk spillovers from a sovereign country $\Delta CoVaR^{j|SOV}$ (8.7 bp) is higher than that from a financial institution $\Delta CoVaR^{j|FI}$ (6.73 bp).

[6] 1 basis point (bp) in the CDS spread accounts for 0.01% of the per-annum notional fee of the CDS contract. An investor A that buys a \$1,000 worth of CDS contract on the underlying bond value of entity B from C at 5 bp pays the entity of issuance (C) \$5 as an annual fee. Should B defaults on its debt, A is repaid by \$1,000 from C. Therefore, when B has a high chance of defaults, C demands high CDS spreads.

In Figure 3.1, we report the VaR measures of financial institutions and sovereign countries, and the risk spillovers of $CoVaR$ and $\Delta CoVaR$ from the sovereign countries to financial institutions. As the figures show, the VaRs of financial institutions peak around late 2008 during the Global Financial Crisis whereas the VaRs of sovereign countries increase in late 2008 but climb up again in around late 2011 to early 2012 for some countries (especially Italy and Spain in the figure, including other European sovereign countries that are considered to be "distressed" at certain stages during the Eurozone Sovereign Crisis). In terms of the $CoVaR$s, the fluctuations around the Eurozone Sovereign Crisis increase as the risks and distresses of the sovereign countries are incorporated into the risk measures, though the influence varies from country to country.

As for the risk spillovers measured as $\Delta CoVaR$s from sovereign countries to financial institutions, patterns vary as Germany's risk contributions are only prominent for a very short time around 2009 whereas Spain, Italy as well as France all had large increase in risk spillovers to the financial institutions. For France and Italy, risk contributions during the Financial Crisis are comparatively smaller than the contributions around the Eurozone Sovereign Crisis which peaked around 2012 when the outlooks for the economic and political status of the European Union were at the most uncertain level. As the several rounds of bail out packages from the European Commission and IMF started help stabilise the distressed economies, combined with the efforts of ECB in providing continuous liquidity support to boost interbank lending, the $\Delta CoVaR$ risk measures started decreasing and stabilising till the end of the sample period of our study.

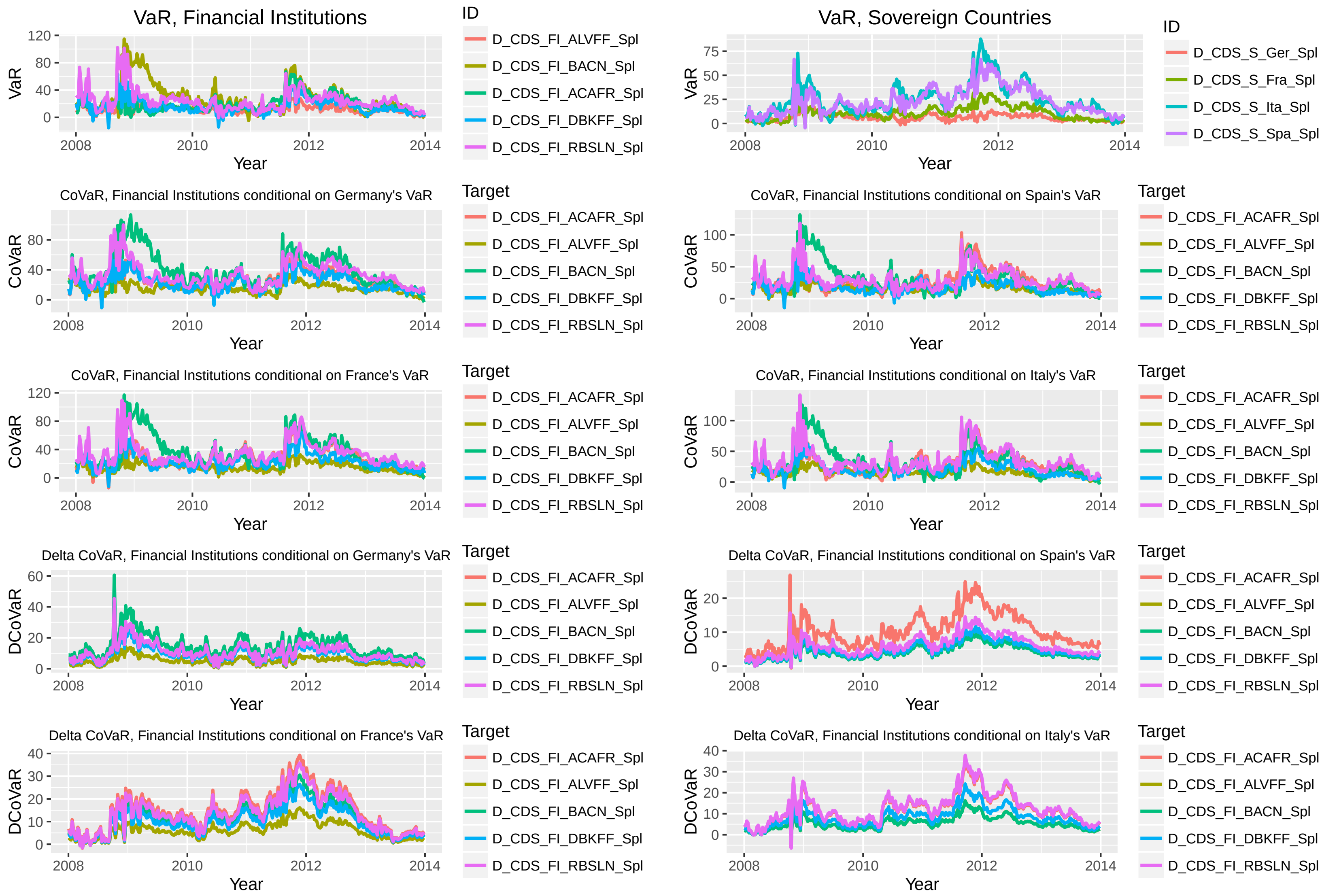

Figure 3.1: **Examples Of Systemic Risk Contribution**.

3.6.2 *CoRisk*

We calculate the weighted sum of the $\Delta CoVaR$s from the same country i to all other financial institution js in the sample, as country i's overall risk spillovers and systemic contributions of *CoRisk*. In Table 3.5 we report the summary statistics for the risk measures. We observe that Italy, Portugal and Spain have the largest median spillover effects (5 bp), followed by Germany and France (4 bp).

Table 3.5: **Descriptive Statistics for** *CoRisk*.

	obs.	mean	sd	median	min	max
Austria	312	3	2	2	0	9
Belgium	312	3	2	3	1	10
Bulgaria	312	3	2	2	0	13
Croatia	312	3	2	2	0	12
Cyprus	312	1	1	1	0	4
Czech_Republic	312	1	2	1	0	9
Denmark	312	3	3	3	1	17
Estonia	312	3	3	1	0	15
France	312	4	2	4	0	10
Germany	312	4	2	4	0	15
Greece	312	2	1	2	0	5
Hungary	312	3	2	2	1	12
Iceland	312	3	4	2	0	27
Ireland	312	4	3	4	0	12
Italy	312	5	3	5	2	14
Latvia	312	3	3	2	0	17
Lithuania	312	4	4	3	1	21
Netherlands	312	3	2	3	0	12
Norway	312	2	2	2	0	12
Poland	312	2	1	2	0	9
Portugal	312	6	4	5	1	16
Slovakia	312	3	3	2	2	17
Slovenia	312	3	1	2	0	7
Spain	312	5	2	5	0	13
Sweden	312	3	3	2	0	14
UK	312	3	2	3	1	11
US	312	2	1	2	1	6
Japan	312	3	1	3	0	8
China	312	2	2	2	0	13

In Figure 3.2 we compare the evolutions of these risk measures between two groups of countries: the "core" European countries[7] that are traditionally considered as the central structure of the European Union without signals of default level distress of their economies; and the "distressed" European countries[8] that have received any forms of financial aid or considered as in economic distresses during the period of our study. In Figure 3.3 we compare the *VaR* of sovereign countries and their *CoRisk* as the comparison between sovereign risk and systemic risk spillovers. In Figure 3.2 we find that there is a positive response of *CoRisk* to the outbreak of Global Financial Crisis in October 2008 which help push up *CoRisk* which decline at the beginning of 2009. *CoRisk* levels rise up again for three consecutive waves following the distresses of the government debts of Greece, Ireland, and Italy, and declines following the bailout packages and austerity measures in May 2010 for Greece, November 2010 for Ireland, and November 2011 for Italy. Comparing *CoRisk* measures within their country groups, the risk contributions of the "core" countries during the Global Financial Crisis and the Eurozone Sovereign Crisis are in a comparable order of magnitude whereas the contributions of the "distressed" group of countries grow significantly higher during the Eurozone Sovereign Crisis than during the Global Financial Crisis, with the exceptions of Greece and Cyprus.

A country's own sovereign risk does not necessarily fully reflected in its risk spillovers, as we find in the case of Greece. In Figure 3.3 we can see the *VaR* of Greece surpassing other *VaR*s by a large degree, signifying the extraordinary level of sovereign risk in Greek government bond and the market fear about the fiscal unsustainability in Greece. However its *CoRisk* level is relatively moderate comparing with other distressed countries such as Italy and Portugal.

[7]Germany, France, Austria, Belgium, the Netherlands and UK

[8]the "GIIPS" countries of Greece, Ireland, Italy, Portugal and Spain, with the addition of Cyprus due to the Cypriot Banking Crisis of 2012-2013

Figure 3.2: **Evolution Of Systemic Risk Contribution For Different Sovereign Countries**.
Figure 3.2 plots the systemic risk spillovers from sovereign countries. The related economic/political events marked on the graphs are recorded in Table A.1.

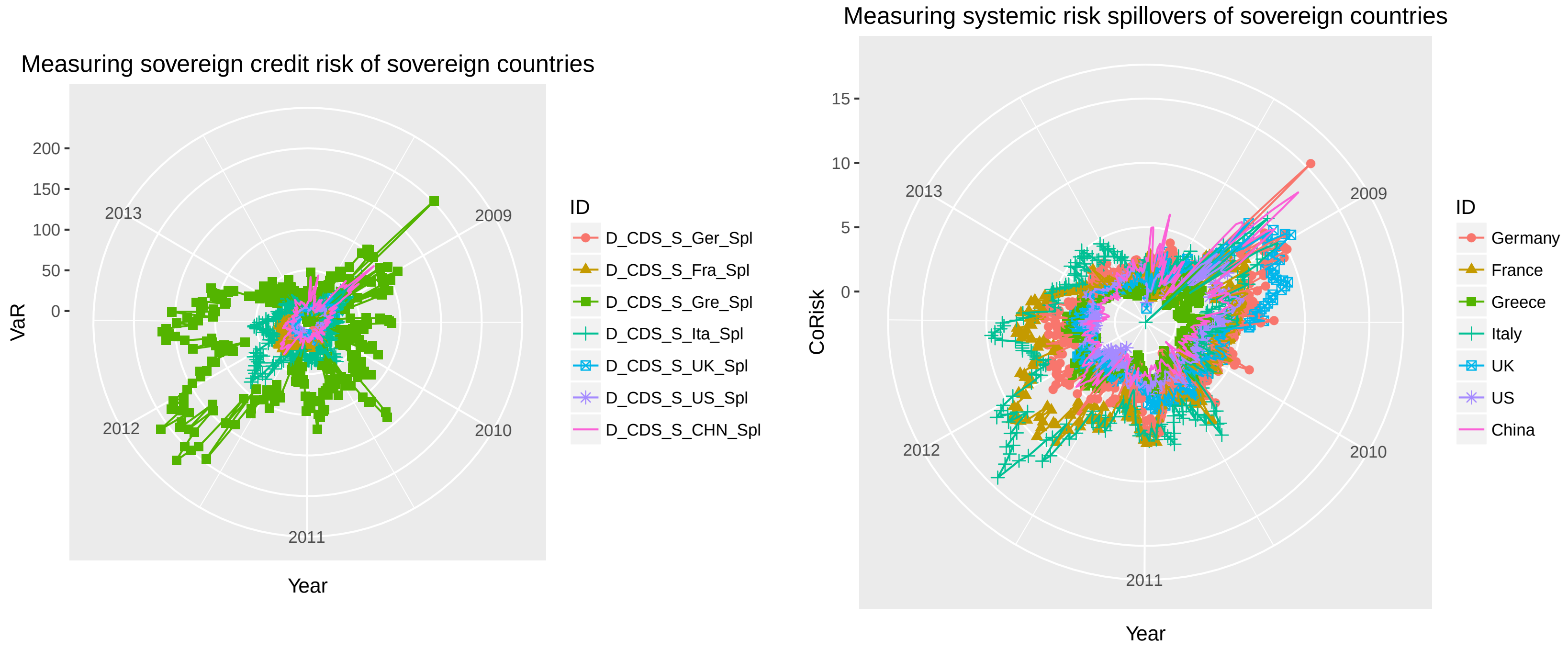

Figure 3.3: **Comparing Sovereign Credit Risk And Systemic Risk Contribution**.

3.7 Disentangling Sovereign Systemic Risk Spillovers

In this section, we investigate the relationships between the systemic risk spillovers of sovereign countries and their macro-financial states, and examine that to what extent can the macro-financial variables of sovereign countries influence their systemic risk spillovers to financial institutions.

We select the `corisk` measures of 23 countries[9] that are member states of the Economic and Monetary Union and collect the respective macro-financial variables regarding these countries.

The specification takes the form of:

$$
\begin{aligned}
corisk_{i,t} =& \beta_1 gdp\_growth_{i,t} + \beta_2 debt_{i,t} + \beta_3 decifit\_surplus_{i,t} + \beta_4 interest\_expenses_{i,t} \\
&+ \beta_5 asset\_relief_{i,t} + \beta_6 guarantees_{i,t} + \beta_7 liquidity_{i,t} + \beta_8 recapitalisation_{i,t} \\
&+ \alpha_i + \gamma_t + u_{i,t} \qquad (3.15)
\end{aligned}
$$

We consider the following country-specific macro-financial variables:

- Macroeconomic indicators regarding economic fundamentals and fiscal sustainability (real GDP growth "`gdp_growth`", interest expenses "`interest_expenses`", deficit/surplus "`deficit_surplus`", government debt "`debt`"). Deficit/surplus and government debt level are measured as proportional to the national GDP level. Interest expenses are measured as proportional to the government revenues, which represents the "cash flow" sustainability of government debt (De Bruyckere et al., 2013). We expect higher levels of these measures would correlate with higher levels of risk spillovers, except "`gdp_growth`" is expected be negatively correlated with risk spillovers.

[9]Austria, Belgium, Bulgaria, Cyprus, Czech Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Poland, Portugal, Republic, Slovakia, Slovenia, Spain, Sweden, the Netherlands, and UK.

- Government intervention measures (“`asset_relief`”, “`guarantees`”, “`recapitalisation`”, “`liquidity`”) in the context of financial crisis. European Commission (2013) publishes the government intervention by each member states during the financial crisis in the form of state aid measures, and we use these state aid measures[10] to assess the actual involvement of sovereign countries in supporting and bailing out distressed financial institutions. Asset relief refers to the relief of impaired assets by the public authority to strengthen the institution’s balance sheet in order to enable its access to liquidity funding. Guarantees refers to the government guarantees schemes including deposit protection and liability guarantees. Recapitalisation refers to the government injection of equity provisions to boost the capital base of the institutions. Liquidity refers to the liquidity measures “other than guarantees on liabilities” (European Commission, 2013), including the liquidity support provided by the ECB. As these measures signify the direct involvement of sovereign countries in supporting their financial markets, we expect greater involvement to be reflected in greater risk spillovers from sovereign countries.

The variables are collected at quarterly frequencies which spans from 2008Q1 to 2013Q4 consisting of 24 quarters. Table 3.6 reports the summary descriptives for these variables.

[10] The technical definitions and implementations of state aid measures are covered in Lannoo and Napoli (2010).

Table 3.6: **Descriptive Statistics for Panel Estimation**.

Variables	Obs.	Mean	Std. dev.
`corisk`	552	0.0549	0.0260
`debt`	552	0.0253	0.0573
`deficitsurplus`	552	-4.7084	5.9497
`interestrevenue`	552	0.0580	0.0337
`gdp_growth`	552	-0.1211	2.5840
`assetrelief`	552	0.0018	0.0059
`guarantees`	552	0.0636	0.1962
`recapitalisation`	552	0.0111	0.0316
`liquidity`	552	0.0050	0.0110

In Table 3.7 we report the regression results for the full sample of EMU countries and in Table 3.8 we report the regression results for the sub-sample of distressed countries (Greece, Ireland, Italy, Portugal, and Spain). We also report the regression results on selected individual countries in Table 3.9 for cross-country comparisons. In Table 3.14 we report the diagnostic tests for the model specifications in Table 3.7. According to the model diagnostics we use Newey-west robust estimators for standard errors, and we use fixed effect models in favour of random effect models.

From the results we find that although the level of public debt and GDP growth have significant explanatory power with expected signs in the full sample, they do not have explanatory power for the distressed country sub-sample, whereas the level of interest expenses has similar explanatory power in both model sets. These findings suggest that although economic fundamentals are risk drivers generally reflected in the risk spillovers from sovereign countries to financial institutions, the spillover effects from distressed countries are reflected more by the market concerns about their fiscal sustainability, of which interest expenses is a more direct measure. For state aid measures, we find the involvement of impaired asset relief by sovereign countries to have a stronger positive effect on the risk spillover relationship than interest expenses, whereas governments' liquidity support in the form of recapitalisation reduces risk spillovers, while other forms of state aid do not have significant effects. The results suggest that recapitalisation is a more effective way in stabilising interbank lending and mitigating market participants' fear about systemic risk. Our findings regarding the fiscal sustainability and state aid measures are in line with the findings in De Bruyckere et al. (2013) where the authors show the existence of sovereign risk spillovers through government intervention channels. In addition, results from individual countries show more significant coefficients for the four state aid measures, though their coefficient values and signs vary by individual cases.

Table 3.7: **Panel Model for Systemic Risk Contributions of Sovereign Countries - Full Sample**

Table 3.7 reports the fixed effect panel regression results on `corisk`. Newey-West heteroskedasticity-autocorrelation-robust estimates of standard errors are reported in parentheses.

	Dependent variable: `corisk`					
	(a1)	(a2)	(a3)	(a4)	(a5)	(a6)
`debt`	0.062***	0.062***	0.063***	0.061***	0.061***	0.062***
	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)	(0.023)
`deficit_surplus`	−0.0002	−0.0003	−0.0002	−0.0002	−0.0003	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
`gdp_growth`	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
`interest_expenses`	0.218***	0.218***	0.223***	0.225***	0.224***	0.236***
	(0.071)	(0.070)	(0.070)	(0.073)	(0.067)	(0.068)
`asset_relief`		0.465***				0.539***
		(0.122)				(0.115)
`guarantees`			−0.005			−0.002
			(0.009)			(0.004)
`liquidity`				−0.176**		−0.218**
				(0.090)		(0.091)
`recapitalisation`					−0.068*	−0.078**
					(0.035)	(0.030)
id FE	YES	YES	YES	YES	YES	YES
time FE	YES	YES	YES	YES	YES	YES
Observations	529	529	529	529	529	529
R^2	0.145	0.149	0.145	0.148	0.151	0.157
Adjusted R^2	0.137	0.141	0.138	0.141	0.143	0.148
F Statistic	21.260***	17.490***	17.050***	17.460***	17.780***	11.590***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.8: **Panel Model for Systemic Risk Contributions of Sovereign Countries - Distressed Countries**

Table 3.8 reports the fixed effect panel regression results on `corisk`. Newey-West heteroskedasticity-autocorrelation-robust estimates of standard errors are reported in parentheses.

	Dependent variable: `corisk`					
	(b1)	(b2)	(b3)	(b4)	(b5)	(b6)
`debt`	0.037	0.037	0.044	0.037	0.030	0.039
	(0.032)	(0.032)	(0.035)	(0.033)	(0.034)	(0.037)
`deficit_surplus`	−0.0001	−0.0001	0.0001	−0.0001	−0.0004	−0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
`gdp_growth`	−0.003	−0.002	−0.003*	−0.003	−0.002	−0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
`interest_expenses`	0.219***	0.213***	0.240***	0.219***	0.235***	0.250***
	(0.084)	(0.082)	(0.084)	(0.085)	(0.073)	(0.071)
`asset_relief`		0.725***				0.730***
		(0.233)				(0.245)
`guarantees`			−0.00005			0.006
			(0.005)			(0.005)
`liquidity`				0.269		0.191
				(0.288)		(0.287)
`recapitalisation`					−0.102***	−0.100***
					(0.034)	(0.032)
id FE	YES	YES	YES	YES	YES	YES
time FE	YES	YES	YES	YES	YES	YES
Observations	138	138	138	138	138	138
R^2	0.163	0.169	0.187	0.163	0.225	0.261
Adjusted R^2	0.151	0.155	0.172	0.150	0.207	0.234
F Statistic	6.240***	5.150***	5.826***	4.957***	7.361***	5.470***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.9: **Systemic Risk Contributions of Sovereign Countries - Individual Cases**

Table 3.9 reports the individual regression results on `corisk`. Newey-West heteroskedasticity-autocorrelation-robust estimates of standard errors are reported in parentheses.

	Dependent variable: `corisk`								
	(c1) Germany	(c2) France	(c3) UK	(c4) Greece	(c5) Ireland	(c6) Italy	(c7) Portugal	(c8) Spain	(c9) Cyprus
`debt`	0.119	0.097	0.011	−0.014	0.218**	−0.121	−0.034	0.242	−0.018
	(0.073)	(0.127)	(0.051)	(0.024)	(0.110)	(0.118)	(0.051)	(0.178)	(0.015)
`deficit_surplus`	0.00001	−0.001	0.00005	0.00002	0.001	0.001	−0.0005	−0.0001	0.0004
	(0.001)	(0.001)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.0002)	(0.0003)
`gdp_growth`	−0.004***	−0.008	−0.006*	−0.001	−0.003*	−0.009***	−0.002	−0.020	−0.003**
	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.013)	(0.001)
`interest_expenses`	−1.309	−0.888	0.087	0.047***	0.538***	0.025	0.233	0.545	0.067
	(1.015)	(1.168)	(0.198)	(0.018)	(0.153)	(0.113)	(0.518)	(0.601)	(0.093)
`asset_relief`	5.577**	15.870	1.935***		0.384		−0.320	7.775***	
	(2.584)	(24.810)	(0.534)		(0.848)		(1.569)	(2.462)	
`guarantees`	1.464	−0.313	0.169***	−0.065***	−0.016	−0.332***	−0.625***	−0.646***	−0.039
	(1.012)	(0.265)	(0.037)	(0.021)	(0.010)	(0.015)	(0.222)	(0.138)	(0.044)
`liquidity`	6.300*		4.367***	−0.874***	0.436		−0.020	−1.580***	
	(4.560)		(0.791)	(0.242)	(5.987)		(0.371)	(0.212)	
`recapitalisation`	−2.305**	1.041	3.140***	−0.097	0.091	−9.009***	0.730**	5.594***	−0.100***
	(1.057)	(1.516)	(0.455)	(0.074)	(0.209)	(0.913)	(0.344)	(2.020)	(0.033)
intercept	−0.029	0.006	−0.032*	0.072***	0.108***	0.074***	0.104***	0.103***	0.036***
	(0.049)	(0.054)	(0.018)	(0.005)	(0.015)	(0.014)	(0.035)	(0.031)	(0.008)
Observations	23	23	23	23	23	23	23	23	23
R^2	0.724	0.467	0.800	0.775	0.830	0.773	0.598	0.745	0.373
Adjusted R^2	0.567	0.219	0.686	0.670	0.734	0.688	0.368	0.600	0.138
Residual Std. Error	0.011	0.018	0.009	0.011	0.014	0.010	0.014	0.015	0.011
F Statistic	4.595***	1.881	7.017***	7.393***	8.570***	9.091***	2.599*	5.120***	1.586

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.8 Structural Stability of the $CoVaR$ Risk Measures

As part of our study on the sovereign risk spillovers from sovereign countries to the financial institutions, we investigate the potential existence of shifting patterns in the risk relationship. Specifically, we consider the existence of structural breaks on the 0.5 and 0.95 quantiles of our models of conditional value of risk based on quantile regressions. We follow the method of Oka and Qu (2011) which extends the structural break analysis of Bai and Perron (1998) to quantile models and estimating multiple structural changes occurring at unknown points in the conditional quantile functions. The test statistics in Oka and Qu (2011) are provided by Qu (2008), which develops the test statistics of structural breaks under a quantile regression framework of Koenker and Bassett Jr (1978).

3.8.1 Methodology

Here we provide a brief overview of the quantile structural break test procedure, and how we incorporate the quantile structural break test into our analysis.

In Koenker and Bassett Jr (1978)'s quantile regression framework, for quantiles $q \in (0, 1)$, the q^{th}-quantile conditional distribution function of a random variable y given regressors x, $Q_y(q|x)$ can be formulated as a function of linear parameters:

$$Q_y(q|x) = X'\beta(q) \tag{3.16}$$

where the coefficients $\beta(q)$ are allowed to be quantile dependent and can be solved by:

$$\min_b \sum_{i=1}^{n} \rho_q(y_i - x_i'b) \tag{3.17}$$

where $\rho_q(.)$ is the check function $\rho_q = u(q - 1(u < 0))$. Assuming that this conditional quantile function is affected by m structural changes at unknown points $(T_1^0, \ldots, T_m^0)$, the function structure can be expressed as a structure of $m+1$ regimes:

$$Q_{y_t} = \begin{cases} x_t'\beta_1^0(q), & t = 1, \ldots, T_1^0, \\ x_t'\beta_2^0(q), & t = T_1^0 + 1, \ldots, T_2^0, \\ \vdots & \vdots \\ x_t'\beta_{m+1}^0(q), & t = T_m^0 + 1, \ldots, T_T, \end{cases} \tag{3.18}$$

The break points $\hat{T}^b = (T_1^0, \ldots, T_m^0)$ and coefficients $\hat{\beta}(q) = (\hat{\beta}_1(q), \ldots, \hat{\beta}_{m+1}(q))'$ in the function structure can be estimated by solving:

$$S_T(q, \beta(q), T^b) = \sum_{j=0}^{m} \sum_{t=T_j+1}^{T_{j+1}} \beta_q(y_t - x_t^q \beta_{j+1}(q)) \tag{3.19}$$

$$(\hat{\beta}(q), \hat{T}^b) = arg \min_{\beta(q), T^b \in \Lambda_\epsilon} S_T(q, \beta(q), T^b) \tag{3.20}$$

where Λ_ϵ is the set of all possible partitions and ϵ is treated as a small positive number:

$$\Lambda_\epsilon = \left\{ (T_1, \ldots, T_m) : T_j - T_{j-1} \geq \epsilon T (j = 2, \ldots, m), T_1 \geq \epsilon T, T_m \leq (1-\epsilon)T \right\} \tag{3.21}$$

We use the SQ_q statistics provided by Qu (2008) as the test statistics for testing structural breaks under a specific quantile. Denote $\|Z\|_\infty = max(z_1, \ldots, z_k)$ for a vector $z = (z_1, \ldots, z_k)$, and the SQ_q statistics is constructed as:

$$
\begin{aligned}
SQ_q &= \sup_{\lambda \in [0,1]} \left\| (q(1-q))^{-1/2} \left[H_{\lambda,T}(\hat{\beta}(q)) - \lambda H_{1,T}(\hat{\beta}(q)) \right] \right\|_\infty \\
H_{\lambda,T}(\hat{\beta}(q)) &= \left(\sum_{t=1}^{T} x_t x_t' \right)^{-1/2} \sum_{t=1}^{[\lambda T]} x_t \psi_q (y_t - x_t' \hat{\beta}(q))
\end{aligned} \tag{3.22}
$$

As for the $SQ_q(l+1|l)$ statistics for testing l breaks against $l+1$ breaks, denote $SQ_{q,j}$ as the SQ_q statistics from the j^{th} segment:

$$
\begin{aligned}
SQ_{q,j} &= \sup_{\lambda \in [0,1]} \left\| (q(1-q))^{-1/2} \left[H_{\lambda,\hat{T}_{j-1},\hat{T}_j}(\hat{\beta}_j(q)) - \lambda H_{1,\hat{T}_{j-1},\hat{T}_j}(\hat{\beta}_j(q)) \right] \right\|_\infty \\
H_{\lambda,\hat{T}_{j-1},\hat{T}_j}(\hat{\beta}_j(q)) &= \left(\sum_{t=T_{j-1}+1}^{T_j} x_t x_t' \right)^{-1/2} \sum_{t=T_{j-1}+1}^{[\lambda(T_j - T_{j-1})]} x_t \psi_q (y_t - x_t' \hat{\beta}(q)) \\
SQ_q(l+1|l) &= \max_{1 \le j \le l+1} SQ_{q,j}
\end{aligned} \tag{3.23}
$$

Similar to the approaches in Bai and Perron (1998), the SQ_q assumes that under the q^{th}-quantile, in an arbitrary partition, there are no structural breaks, and when the test statistics yields a sufficiently large value (compared to the simulated critical values provided in Qu (2008)) the null hypothesis is rejected in favour of the existence of 1 structural break occurring at the partition location. The test against more breaks $l+1$ in any sub-partitions of the current l partitions is then carried out until the maximum number of breaks is found ($SQ_q(l+1|l)$ falls below the critical value) in the sample period.

3.8.2 Implementation Strategy

Using the method discussed above, we examine the 1470 *CoVaR* series representing the systemic risk spillover effects from 30 sovereign countries to the 49 financial institutions in our study sample. Specifically for the purpose of examining the occurrence of structural breaks, we estimate the $CoVaR$ series that are estimated from the Thomson Reuters CDS data from January 2008[11] to October 2014 in weekly frequency with 357 observations for each series.

In order to incorporate the analysis of quantile structural change into our main framework, we first conduct the SQ_q test on all regression models in order to identify the existence and location of structural regimes, as well as the estimates of coefficient parameters inside each regime. Specifically, we examine the existence of structural breaks over quantiles $q \in \{0.5, 0.75, 0.9, 0.95, 0.95\}$, as the quantile estimates at $q = 0.50$ and $q = 0.95$ are the interests of analysis in $\Delta CoVaR$ and we use other quantiles for comparisons.

3.8.3 Results

We carry out quantile structural break analysis on the regression equations for all combinations of "financial institution | sovereign country" pairs and the five upper quantiles. In the cross-section dimension, we report the number of break occurrence in our sample in Table 3.10 and the occurrence breakdown by originator countries in Figure 3.4. In the time-horizon dimension, we report the occurrence of breaks over the sample period in Figure 3.5 by the n^{th} occurrence and Figure 3.6 by the originator countries.

[11] As discussed earlier in Section 3.4, the CDS series in our sample are spliced from two sources using the technique provided by Thomson Reuters CDS and is discussed in Buchholz and Tonzer (2013). Here we examine the structural break occurrence from the one data source in order to avoid introducing breaks by our splicing of the series.

Table 3.10: **Distribution of breaks over quantiles**

Quantile	No. of total Eqs	with 1 break	with 2 breaks	with 3 breaks
0.50	1,470	41	18	6
0.75	1,470	47	12	5
0.90	1,470	39	26	16
0.95	1,470	45	40	38
0.99	1,470	1	0	0

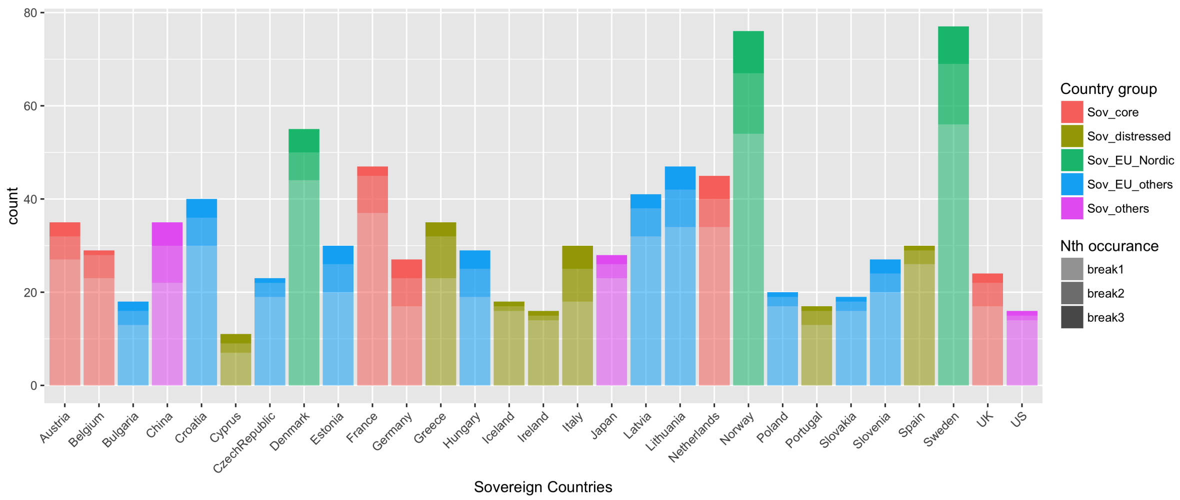

Figure 3.4: **distribution of breaks over source countries**

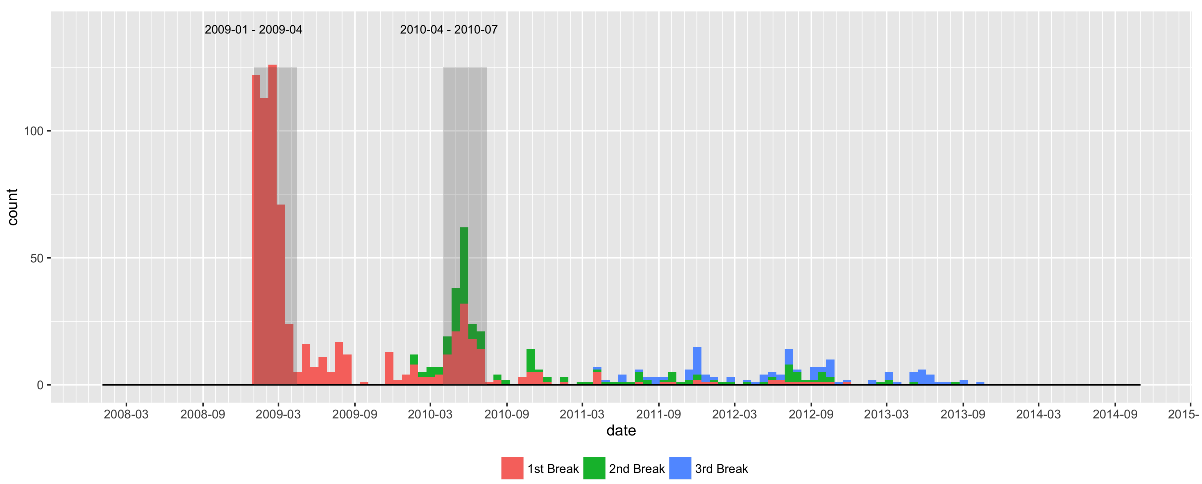

Figure 3.5: **distribution of breaks over sample period - n^{th} occurrence**

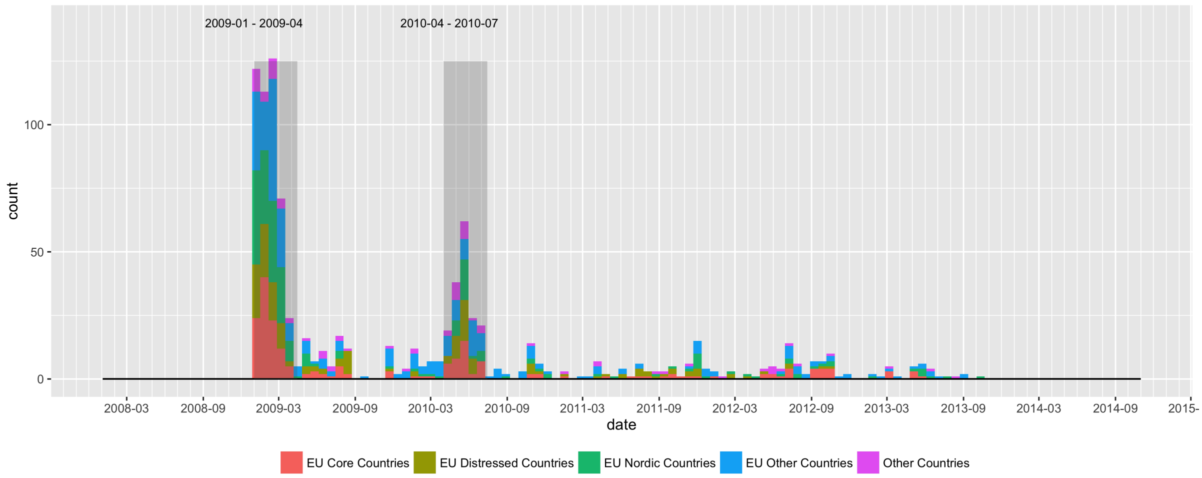

Figure 3.6: **distribution of breaks over sample period - source of spillovers**

As reported in Table 3.10, the test routine found 41 equations on the median quantile to be affected by at least 1 break, and 45 equations with at least 1 break on the 0.95 quantile. The occurrence of breaks are relatively similar in other quantiles as well. However it is worth noting that for models that are found to contain breaks, it is easier to be detected under 0.95 quantile to have more than one breaks. The results from Figure 3.4 and Figure 3.5 show that the structural breaks occur more often in models related to Nordic countries than other countries, and around the two periods: January 2009 - April 2009, and April 2010 - July 2010. The first period is related to the spreading of impact from the Global Financial Crisis whereas the second period is related to the initial outbreak of the Eurozone Sovereign Crisis with the first bailout of Greece. Therefore the occurrence of structural breaks which imply the shift in the relationships of risk spillovers of $CoVaR$ relate to the peak periods of market distress, which suggests that common market distress has an impact on the risk spillovers between sovereign countries and financial institutions, the external shifting effect of which is more apparent the $CoVaR$s from country groups such as the Nordic countries.

The general findings from our examination of the potential occurrence of structural breaks in the quantile models of $CoVaR$ suggest that only very minor portions (2.7% in the median state and 3.1% under 0.95 quantile) are subjected to the shifting of risk patterns during the sample period. Therefore according to the findings there is no need for us to control for systematic structural changes in our model settings, and the findings confirm that our risk measures are robust.

3.9 Conclusions

In this study, we examine the systemic risk spillovers from sovereign countries to financial institutions. Towards this end, we use Adrian and Brunnermeier (2016)'s Conditional Value-at-Risk and $\Delta CoVaR$ methodology to measure the systemic risk spillovers from sovereign CDS market to the CDS market for financial institutions. We construct risk measures around the $\Delta CoVaR$ methodology using credit default swaps data of sovereign countries and financial institutions. We then further investigate the macro-financial determinants of the systemic risk spillovers by examining the relationship between $CoRisk$ measures and the macroeconomic and financial health of the sovereign economies, as well as the countries' involvement in bailing out the financial institutions.

In our analytical framework of CDS market spillovers, the $\Delta CoVaR$ approach allows us to measure the impact of the sovereign distress, as revealed by the sovereign CDS spreads, on the CDS spreads of the financial institutions. One of the advantages in using the $\Delta CoVaR$ risk measures is that it distinguishes the effects of risk spillovers from entity i (as measured by $\Delta CoVaR^{j|i}$ and the weighted $\Delta CoRisk^{i}$), from effects of financial collapse of entity i (as measured by VaR^{i}). As our results show, in the case of Greece, while the VaR of its CDS spreads is high, the potential effects of the default of Greece sovereign bonds are limited as compared with other distressed countries such as Italy and Spain, during their respective distressed event periods. Since the outbreak of distress event of Greek government bonds in May 2010, financial institutions had tried to limit their exposures to Greek government bonds and are required to publicly report their exposures to the European sovereign countries in financial reports and stress tests. Therefore, despite the high default risk for the Greek government bonds, the exposures from private investors have been effectively reduced and we also observe no major market disruption during the technical default for the Greek government bonds during March 2012. Nevertheless, the substantial evidence of the risk spillovers from Spain and Italy from our results justify the bailout package support from the "troika" (European Commission, ECB and IMF) in order to prevent the potential market collapse from sovereign credit risk. This range of results is also supported by previous studies in sovereign risk spillovers such as Fong and Wong (2012); Gray (2013) as well as in the studies on the economic fundamentals and contagion components in risk spreads such as Gibson, Hall and Tavlas (2012); Beirne and Fratzscher (2013); Meine, Supper and Weiß (2016). As our findings suggest systemic risk spillovers decline as soon as market confidence recover, efforts in stabilising economies and financial markets help reduce the market's perception of the riskiness of the entities as well as the risk spillovers among the entities. In this sense our findings support the bailout packages by the "troika" in stabilising market confidence and promoting fiscal sustainability by austerity measures.

In terms of policy implications, we support De Bruyckere et al. (2013)'s call to establish union-level distress response mechanisms as individual country's response to troubles in its financial market is found to increase systemic risk spillovers as market's fear about its fiscal sustainability intensify. Therefore our findings support establishing union-level financial safety net and resolution mechanisms in the European Union such as the European Financial Stability Facility (EFSF) and European

Financial Stabilisation Mechanism (EFSM).

Appendix 3.A Appendix

Table 3.11: **CDS Series for Sovereign Country CDS Spreads**

series	name	groups
scds_ger_spl	Germany	EU_core
scds_fra_spl	France	EU_core
scds_aus_spl	Austria	EU_core
scds_bel_spl	Belgium	EU_core
scds_neth_spl	Netherlands	EU_core
scds_cyp_spl	Cyprus	EU_distressed
scds_gre_spl	Greece	EU_distressed
scds_ice_spl	Iceland	EU_distressed
scds_ita_spl	Italy	EU_distressed
scds_por_spl	Portugal	EU_distressed
scds_spa_spl	Spain	EU_distressed
scds_ire_spl	Ireland	EU_distressed
scds_den_spl	Denmark	EU_Nordic
scds_swe_spl	Sweden	EU_Nordic
scds_nor_spl	Norway	EU_Nordic
scds_bul_spl	Bulgaria	EU_others
scds_cro_spl	Croatia	EU_others
scds_cze_spl	CzechRepublic	EU_others
scds_lat_spl	Latvia	EU_others
scds_est_spl	Estonia	EU_others
scds_hun_spl	Hungary	EU_others
scds_lit_spl	Lithuania	EU_others
scds_pol_spl	Poland	EU_others
scds_slk_spl	Slovakia	EU_others
scds_slv_spl	Slovenia	EU_others
scds_uk_spl	UK	EU_core
scds_us_spl	US	others
scds_jp_spl	Japan	others
scds_chn_spl	China	others

Table 3.12: **CDS Series for Corporate CDS Spreads**

Series	Name	Groups	Home country
ccds_i_alvff_spl	Allianz	insurer	Germany
ccds_i_gmi_spl	Assicurazioni Generali	insurer	Italy
ccds_i_avln_spl	Aviva	insurer	UK
ccds_i_csfr_spl	AXA	insurer	UK
ccds_i_pruln_spl	Prudential UK	insurer	UK
ccds_i_aign_spl	AIG	insurer	US
ccds_i_metn_spl	Metlife	insurer	US
ccds_i_prun_spl	Prudential US	insurer	US
ccds_b_cbaau_spl	Commonwealth Bank Of Australia	bank	Australia
ccds_b_ebsvi_spl	Erste Group Bank - Australia	bank	Australia
ccds_b_nabau_spl	National Australia Bank Limited	bank	Australia
ccds_b_kbcbt_spl	KBC GROEP NV - Belgium	bank	Belgium
ccds_b_bocsh_spl	Bank of China	bank	China
ccds_b_dansko_spl	DANSKE BANK A/S - Denmark	bank	Denmark
ccds_b_acafr_spl	Credit Agricole	bank	France
ccds_b_bnpfr_spl	BNP Paribas	bank	France
ccds_b_glefr_spl	Societe Generale	bank	France
ccds_b_cbkff_spl	Commerzbank AG - Germany	bank	Germany
ccds_b_dbkff_spl	Deutsche Bank	bank	Germany
ccds_b_bmpsmi_spl	Banca Monte Dei Paschi - Italy	bank	Italy
ccds_b_ispmi_spl	Intesa Sanpaolo - Italy	bank	Italy
ccds_b_ucgmi_spl	Unicredito Italiano	bank	Italy
ccds_b_daiwto_spl	Daiwa Securities Group Inc - Japan	bank	Japan
ccds_b_mizhto_spl	Mizuho	bank	Japan
ccds_b_sumito_spl	Sumitomo Mitsui	bank	Japan
ccds_b_ingaae_spl	ING Bank	bank	Netherlands
ccds_b_wbcau_spl	Westpac Banking Corp - New Zealand	bank	New Zealand
ccds_b_bbvamc_spl	BBVA	bank	Spain
ccds_b_popmc_spl	Banco Popular Espanol SA - Spain	bank	Spain
ccds_b_sanmc_spl	Banco Santander	bank	Spain
ccds_b_ndask_spl	Nordea Bank - Sweden	bank	Sweden
ccds_b_shbask_spl	Svenska Handelsbanken AB - Sweden	bank	Sweden
ccds_b_swedask_spl	Swedbank AB - Sweden	bank	Sweden
ccds_b_csgnvx_spl	Credit Suisse	bank	Switzerland
ccds_b_ubsnvx_spl	UBS - Switzerland	bank	Switzerland
ccds_b_barcln_spl	Barclays	bank	UK
ccds_b_hsbaln_spl	HSBC Bank	bank	UK
ccds_b_lloyln_spl	LLoyds Banking group	bank	UK
ccds_b_rbsln_spl	RBS	bank	UK
ccds_b_stanln_spl	Standard Chartered	bank	UK

Continued on next page

Table 3.12 – *Continued from previous page*

Series	Name	Groups	Home country
`ccds_b_bacn_spl`	Bank of America	bank	US
`ccds_b_citin_spl`	Citigroup	bank	US
`ccds_b_cofn_spl`	Capital One Financial	bank	US
`ccds_b_gsn_spl`	Goldman Sachs	bank	US
`ccds_b_jpmjn_spl`	JP Morgan	bank	US
`ccds_b_msn_spl`	Morgan Stanley	bank	US
`ccds_b_wfcn_spl`	Wells Fargo	bank	US

Table 3.13: **Variable Correlations**

Table 3.13 reports the correlation tables for the variables used in the panel regressions in Section 3.7. Variable symbols are listed below: A: `spillovers`; B: `debt`; C: `deficitsurplus`; D: `gdp_growth`; E: `interestrevenue`; $F1$: `assetrelief`; $F2$: `guarantees`; $F3$: `liquidity`; $F4$: `recapitalisation`.

	A	B	C	D	E	$F1$	$F2$	$F3$	$F4$
A	1	0.155	-0.007	-0.223	0.085	0.048	-0.020	-0.032	-0.134
B	0.155	1	-0.298	-0.327	0.053	0.042	0.173	0.138	0.102
C	-0.007	-0.298	1	0.097	0.340	-0.188	-0.182	-0.158	-0.386
D	-0.223	-0.327	0.097	1	0.033	0.039	-0.067	-0.163	-0.063
E	0.085	0.053	0.340	0.033	1	-0.083	-0.142	-0.131	-0.263
$F1$	0.048	0.042	-0.188	0.039	-0.083	1	0.012	0.122	0.160
$F2$	-0.020	0.173	-0.182	-0.067	-0.142	0.012	1	-0.025	0.304
$F3$	-0.032	0.138	-0.158	-0.163	-0.131	0.122	-0.025	1	0.024
$F4$	-0.134	0.102	-0.386	-0.063	-0.263	0.160	0.304	0.024	1

Table 3.14: **Diagnostic Tests for Panel Models**
Table 3.14 reports the diagnostic test results for panel model specifications used in Table 3.7. We use Breusch-Pagan tests to examine the presence of heteroskedasticity and Hausman tests for the consistency of random effect estimators versus fixed effect estimators.

Breusch-Pagan Homoskedasticity Test	H0: Model error is homoskedastic
(a1)	$BP = 82, df = 5, p = 3e - 16$
(a2)	$BP = 85, df = 6, p = 4e - 16$
(a3)	$BP = 83, df = 6, p = 8e - 16$
(a4)	$BP = 83, df = 6, p = 8e - 16$
(a5)	$BP = 85, df = 6, p = 3e - 16$
(a6)	$BP = 88, df = 9, p = 4e - 15$
Hausman test for fixed effects	H0: fixed and random effect estimates are both consistent; prefers random model
(a1)	$chisq = 158.2, df = 5, p = 2.336e - 32$
(a2)	$chisq = 148.3, df = 6, p = 1.787e - 29$
(a3)	$chisq = 160.6, df = 6, p = 4.523e - 32$
(a4)	$chisq = 158.9, df = 6, p = 1.03e - 31$
(a5)	$chisq = 164.4, df = 6, p = 6.816e - 33$
(a6)	$chisq = 148.9, df = 9, p = 1.471e - 27$

Chapter 4

Examining Cross-border Sovereign Distress Spillovers

4.1 Introduction

As a greatest social, political and economic integration in modern Europe, the European Union has witnessed the shocks of both the Global Financial Crisis in 2008 and the Eurozone Sovereign Crisis in 2011. Both crises tested the robustness of such a grand project and also revealed the problems of a politically driven integration, among which, the differences of economic structures of different regions in the EU. Ireland bailed out its banking sector during the Global Financial Crisis at massive cost, and the sudden economic downturn caused the financial markets to question the fiscal sustainability of Greece, Italy, Portugal and Spain given the high levels of public debts and/or competence of their economies, which triggered the Eurozone Sovereign Crisis, putting the said countries at a downward spiral as contagion spread and financial liquidity dried up, also tested the resolve of the member countries in terms of supporting the Union. The Union is formed based on the member countries' shared socio-political values and economic interdependencies, however the crises revealed the heterogeneity among the member countries which might turn out to be greater than previously imagined by policy-makers and academics. Despite this, the crisis episodes provide a precious opportunity for policy-makers and academics to explore the dynamics of economics downturn and spillovers within a cross-economy framework, from a developed economies perspective.

In this study we aim at contributing to the literature on transmission of shocks and spillovers of different financial markets by exploring the dynamics of the fiscal distress in the European Union using a global framework that can allow for full dynamics within countries, between different countries and markets, and in the entire global system as a whole. To this end, we adopt the Global Vector-Autoregressive model (*GVAR*) proposed by Pesaran et al. (2004) and Dees et al. (2007), and examine the dynamics of risk transmissions of fiscal distress of the European Union countries to three destinations: the sovereign bonds market, the sovereign credit default swaps market, and the national banking sector.

The *GVAR* framework is proposed by Pesaran et al. (2004) and with empirical development followed by Dees et al. (2007). As individual economies in a wider system are interlinked through various channels (resources, political and technological developments, cross-border flows of goods, services and financial assets) in a complex way, it is crucial for economic models to take these interlinked effects into account and the *GVAR* provides an appealing approach. Comparing with other large dimensional modelling systems, such as the factor-augmented *VAR* (*FAVAR*, Bernanke, Boivin and Eliasz 2004; Stock and Watson 2005), the *GVAR* modelling approach, which consists of country-specific $VARX^*$ models with foreign influences as unobserved common factors in a multi-country framework, provides a simple, compact and economicly-intuitive approach for high dimensional modelling (Chudik and Pesaran, 2014).

Our research strategy is as follows. First we construct a $VARX^*$ model for each country of our sample with their country-specific endogenous variables as well as foreign counterparts treated as weakly exogenous variables. These $VARX^*$ models will be used to construct the global model ($GVAR$). We then explore the dynamics of risk transmissions through different scenarios in dynamic analysis using generalised impulse response functions ($GIRF$s) and generalised forecast error variance decompositions ($GFEVD$s).

The contribution of our study is as follows:

Firstly, traditional studies on the market price discovery as in Ammer and Cai (2011); Aizenman et al. (2013); Delatte, Gex and López-Villavicencio (2012) focus on the time series properties of the market series of several categories (CDS market, bond market and stock market). In addition, previous studies are often limited by their research scope in country level or in market level, without a unifying framework for policy-makers to extend their findings to alternative scenarios. We investigate the dynamic impact of these markets from country level, country group level as well as system level, using the high dimensional analytical framework of $GVAR$ in Pesaran et al. (2004); Dees et al. (2007), which allows us to understand the sovereign risk impact in the Eurozone Sovereign Crisis in a multi-layered yet sensible approach.

Secondly, the previous studies in the $GVAR$ framework are mostly conducted from a macroeconomic perspective where the countries in the model system are represented by the relative weights of trade volumes, and this approach is continued to the analyses from a financial perspective (Caporale and Girardi, 2013, such as). We address this with a continuous weighting scheme where markets and countries are represented by their pairwise financial claims, which better capture the dynamics in risk spillovers from the sovereign CDS markets, sovereign bond markets, and equity markets.

The rest of the sections are structured as below: We discuss the strands of literature that is relevant to our study in Section 4.2. We describe the methodology implementation of the *GVAR* model in Section 4.3, and describe the selection of data and samples in Section 4.4. In Section 4.5 we discuss the preliminary empirical results and diagnostics of the model and in Section 4.6 we conduct dynamic analysis based on model results. Lastly, in Section 4.7 we summarise the findings of our research.

4.2 Related Literature

The *GVAR* model has been widely adopted in the macroeconomic literature to study the dynamic effects when domestic, foreign and global impact needs to be taken into consideration. For relevant studies in the literature of sovereign risk spillovers, Gray (2013) analyses interactions between banking sector risk, sovereign risk, corporate sector risk and others for European economies and the United States in a $CCA-GVAR$ model and investigate the impact of sovereign distress in Spain and Italy. Gross and Kok (2013) uses a mixed-cross-section sample of countries and banks to investigate contagion among sovereign countries and banks and showed that the system of banks and states has become closely connected over time. Favero (2013) investigates the government bond spreads of the Euro area comparing the results using a traditional *VAR*-based model and a *GVAR* model, and the study shows that the *GVAR* model captures exchange rate depreciation fluctuations as another factor which is not captured by the traditional *VAR* model. We contribute to the literature by examining the three financial markets (sovereign bond markets, sovereign CDS markets and country-specific banking sector), their dynamics and interactions, and also the interconnectedness of countries in these markets.

In terms of relevant studies using the *GVAR* model in the context of sovereign spillovers to financial markets, Alessandri et al. (2009) examines the impact of the defaults of financial institutions to the economic output. However the study is limited to the UK economy and we extend the scope to examine the impact of fiscal distress to the financial sector in the context of a European Union setting. Caporale and Girardi (2013) studies the interactions of sovereign distress represented by the shocks to national bond yield, and we provide an extension to their studies by considering the realisation of systemic risk in the financial sector from macroeconomic shocks. In addition, whereas Caporale and Girardi (2013) and other studies that focus on the macroeconomic aspects of country dynamics use bilateral trade as weighting matrices, we use the time-varying bilateral exposures of the banking sector as the weighting matrices which allows the model to better capture the dynamics in the financial markets. We also contribute to the literature of market risk spillovers (Longstaff et al., 2011; De Bruyckere et al., 2013) by providing evidence to the dynamics of financial market interactions and risk transmissions in the context of sovereign risk spillovers.

4.3 Methodology

Constructing the $GVAR$ framework can be summarised as a two-step approach. In the first step, we construct a country-specific $VARX^*$ structure with the country-specific variables as the endogenous variables and weighted foreign variables from other countries as the exogenous variables. In the second step, each individual $VARX^*$ models are stacked as solved simultaneously as one large $GVAR$ system.

4.3.1 Country-specific $VARX^*$ models

In the $GVAR$ system we consider $i = 0, 1, ..., N$ countries, each represented by a $VARX^*(p_i, q_i)$ structure as:

$$\boldsymbol{x}_{it} = \sum_{l=1}^{p_i} \boldsymbol{\Phi}_{il} \boldsymbol{x}_{i,t-l} + \boldsymbol{\Lambda}_{i0} \boldsymbol{x}^*_{it} + \sum_{l=1}^{q_i} \boldsymbol{\Lambda}_{il} \boldsymbol{x}^*_{i,t-l} + \boldsymbol{u}_{it} \tag{4.1}$$

where $\boldsymbol{x}_{it}$ is a $k_i \times 1$ vector of k_i domestic variables and $\boldsymbol{x}^*_{it}$ is a $k^*_i \times 1$ vector of k^*_i associated foreign variables. $\boldsymbol{x}^*_{it}$ is the cross-sectional weighted average of the other domestic variables as $\boldsymbol{x}^*_{it} = \sum_{j=1}^{N} w_{ij} \boldsymbol{x}_{it}; w_{ij} \leq 0, \sum_{j=1}^{N} w_{ij} = 1, w_{ii} = 0$. $\boldsymbol{u}_{it} \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{ii})$; for $t = s$, $E(\boldsymbol{u}_{it}, \boldsymbol{u}'_{js}) = \boldsymbol{\Sigma}_{ij}$, and for $t \neq s$, $E(\boldsymbol{u}_{it}, \boldsymbol{u}'_{js}) = \boldsymbol{0}$. In essence, the country-specific endogenous "domestic variables" depend on their previous values as well as foreign influences represented by "foreign variables", which are treated as weakly exogenous[1].

The $VARX^*(p_i, q_i)$ can be rewritten into an error correction form $VECMX^*(p_i, q_i)$ to allow the possibility of co-integration relationships within the domestic variables. The lag orders p_i and q_i will be selected according to Akaike information criteria (AIC) for each $VECMX^*(p_i, q_i)$ structure. The country-specific $VECMX^*(p_i, q_i)$ model can then be estimated conditional on the weakly exogenous variables $\boldsymbol{x}^*_{it}$ using reduced rank regression (Harbo, Johansen, Nielsen and Rahbek, 1998; Pesaran, Shin and Smith, 2000).

$$\Delta \boldsymbol{x}_{it} = \boldsymbol{\Lambda}_{i0} \Delta \boldsymbol{x}^*_{it} - \boldsymbol{\Pi}_i \boldsymbol{z}_{i,t-1} + \sum_{l=1}^{p} \boldsymbol{H}_{il} \Delta \boldsymbol{z}_{i,t-1} + \epsilon_{it} \tag{4.2}$$

where $\boldsymbol{z}_{it} \equiv (\boldsymbol{x}'_{it}, \boldsymbol{x}^{*\prime}_{it})'$ is the domestic-foreign variable pair for country i.

[1] The weak exogeneity assumption of the $VARX^*$ model imply the foreign equivalents of the domestic variables do not have long-term influences from the domestic variables, which means that the foreign variables are weakly exogenous to domestic variables in the long-run.

4.3.2 *GVAR* model

Given the country-specific $VECMX^*$ models in (4.2), a "link" matrix $\boldsymbol{W}_i$ will then be used to establish the link between the country-specific pair $\boldsymbol{z}_{it}$, and the collection of all the domestic variables in the system $\boldsymbol{x}_t = (\boldsymbol{x}'_{0t}, \boldsymbol{x}'_{1t}, \ldots, \boldsymbol{x}'_{Nt})'$. $\boldsymbol{W}_i$ is a $(k_i + k_i^*) \times k$ matrix constructed using cross-country weights $w_{ij}, \forall i, j = 0, 1, ..., N$ which satisfies:

$$\boldsymbol{z}_{it} = \boldsymbol{W}_i \boldsymbol{x}_t \tag{4.3}$$

The link matrix $\boldsymbol{W}_i$ contains the weight w_{ij} which reflects the relative importance of country j for country i's economy, and all cross-sectionally weighted foreign variables enter the country-specific $VARX_{p_i,q_i}$ structure by the link matrix. Pooling foreign variables by the link matrix serves as proxies of unobserved common factors, which, as discussed by Chudik and Pesaran (2014), provides a "relatively simple yet effective way of modelling complex high-dimensional systems", something that standard *VAR* procedures cannot accommodate. With the link matrix, the country-specific structure can be written as:

$$\boldsymbol{A}_{i0}\boldsymbol{W}_i\boldsymbol{x}_t = \boldsymbol{a}_{i0} + \boldsymbol{A}_{i1}\boldsymbol{W}_i\boldsymbol{x}_{t-1} + ... + \boldsymbol{A}_{ip_i}\boldsymbol{W}_i\boldsymbol{x}_{t-p_i},\ i = 0, 1, 2, ...N \tag{4.4}$$

Stacking up the $N + 1$ structures leads to a global *GVAR* equation, where the weakly exogenous foreign variables of each country-specific structure are treated as endogenous within the *GVAR* system:

$$\boldsymbol{G}_0\boldsymbol{x}_t = \boldsymbol{a}_0 + \sum_{l=1}^{p} \boldsymbol{G}_l\boldsymbol{x}_{t-l} + \boldsymbol{u}_t,\ p = max(p_i),\ \forall i \tag{4.5}$$

Further transformation leads to (4.6) and its compact form in (4.7):

$$\boldsymbol{x}_t = \boldsymbol{b}_0 + \boldsymbol{F}_1\boldsymbol{x}_{t-1} + \cdots + \boldsymbol{F}_p\boldsymbol{x}_{t-p} + \boldsymbol{\epsilon}_t \tag{4.6}$$

$$\boldsymbol{b}_0 = \boldsymbol{G}_0^{-1}\boldsymbol{a}_0,\ \boldsymbol{F}_j = \boldsymbol{G}_0^{-1}\boldsymbol{G}_j,\ j = 1, \ldots, p,\ \boldsymbol{\epsilon}_t = \boldsymbol{G}_0^{-1}\boldsymbol{u}_t$$

$$\boldsymbol{X}_t = \boldsymbol{F}\boldsymbol{X}_{t-1} + \boldsymbol{E}_t \tag{4.7}$$

4.3.3 Modelling Dynamics

Pesaran and Shin (1998) provides a generalised impulse response analysis ($GIRF$) method that is invariant to the ordering of variables in the VAR model. As discussed in Chudik and Pesaran (2014), in order to identify all $k \times 1$ orthogonal shocks, a large number of restrictions $O(k^2)$ is required, however current literature on macroeconomics does not provide a comprehensive guidance on how the origins of all the shocks should be identified in all sectors of the economic system. The $GIRF$ approach does not rely on structural identification exercises, but considers a counterfactual exercise where the historical correlations of shocks are assumed to be given. This method is well suited for the $GVAR$ model since the model allows for the contemporaneous correlations between u_{it} and $u_{j\neq i,t}$, the shocks to each country-specific $VARX^*$ structure.

Given the model in (4.5), the n-step ahead $GIRF$s of one standard error shock at period t to the l^{th} $VARX^*$ structure on the j^{th} variable is defined as:

$$\begin{aligned} GIRF(\boldsymbol{x}_t; u_{ilt}; n) &= \mathbb{E}(\boldsymbol{x}_{t+n}|u_{ilt} = \sqrt{\sigma_{ii,ll}} I_{t-1}) - \mathbb{E}(\boldsymbol{x}_{t+n}|I_{t-1}) \\ &= \frac{\boldsymbol{\epsilon}_j' \boldsymbol{A}_n \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma}_u \boldsymbol{\epsilon}_l}{\sqrt{\boldsymbol{\epsilon}_j' \boldsymbol{\Sigma}_u \boldsymbol{\epsilon}_l}}, n = 0, 1, 2, \ldots; l, j = 1, 2, \ldots, k \end{aligned} \tag{4.8}$$

Specifically, the generalised forecast error variance decomposition ($GFEVD$) is defined as the proportion of the n-step ahead forecast error variance of the l^{th} element of $\boldsymbol{x}_t$ due to the innovations in the j^{th} element of $\boldsymbol{x}_t$.

$$GFEVD(\boldsymbol{x}_{(l)t}; u_{(j)t}, n) = \frac{\sigma_{jj}^{-1} \sum_{s=0}^{n} (\boldsymbol{\epsilon}_l' \boldsymbol{A}_s \boldsymbol{G}_0^{-1} \boldsymbol{\sigma}_u \boldsymbol{\epsilon}_j)^2}{\sum_{s=0}^{n} \boldsymbol{\epsilon}_l' \boldsymbol{A}_s \boldsymbol{G}_0^{-1} \boldsymbol{\sigma}_u \boldsymbol{G}_0^{-1\prime} \boldsymbol{A}_s' \boldsymbol{\epsilon}_l}, n = 0, 1, 2, \ldots; l = 1, \ldots, k \quad (4.9)$$

4.4 Data

4.4.1 Choice of Countries

For the purpose of this study we select 14 countries that are members of the European Union[2] including: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom.

Among these 14 countries, 11 of them are members of the European Monetary Union, with the rest (Denmark, Sweden and United Kingdom) having their own currencies. Specifically, we consider two country groups for the purpose of our study: "core countries" consisting of Austria, Belgium, Germany, France, Netherlands, and United Kingdom; and "distressed countries" consisting of Greece, Ireland, Italy, Portugal, and Spain.

4.4.2 Choice of Variables

For each country-specific model $VARX^*_{p_i,q_i}$, there are three types of variables. "domestic" variables are country-specific variables that are treated to be endogenous in the model, "foreign" variables are constructed using weighted-averaged values of

[2] We select the sample according to the definition criteria of "EU15", except Luxembourg, according to Eurostat (http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:EU_enlargements). "EU15" country groups are the member state countries that joined the European Union prior to EU's 2004 enlargement. We exclude Luxembourg from the sample, due to the relative small size of its economy and lack of diversity in its financial sector such as no credit default swaps on its sovereign bonds available.

the "domestic" variables of other countries and are treated as weakly-exogenous, and "global" variables are variables reflecting global trends which are not country-specific and are also treated as weakly-exogenous.

For "domestic" variables of each Country i, with $i = 0, ..., 13$, we include its economic growth (measured by growth of GDP, $y_{i,t}$), fiscal sustainability (measured by debt/GDP ratio, $debt_{i,t}$), and three channels of sovereign distress: sovereign bond market, sovereign CDS market, and banking sector equity market (measured by long-term sovereign bond spreads, $r_{i,t}$, 5-year sovereign CDS spreads, $scds$, and the returns of equity index of the banking sector, $seq_{i,t}$).

The "foreign" variables of Country i ($r^*_{i,t}$, $scds^*_{i,t}$, and $seq^*_{i,t}$), are constructed from the weighted-averaged values of equivalent "domestic" variables of other countries (excluding Country i) in the sample. As the purpose of our study is to investigate the financial linkages among countries, we choose Country i's banking sector risk exposure to another Country j's banking sector exposure obtained from Bank of International Settlements[3] as w_{ij}. w_{ij} is then normalised for all js so that the weights are summed to unity when constructing the "foreign" variables. Different from classical $GVAR$ literature that use bilateral trade flows as cross-sectional static weights, our use of cross-country exposure of banks as time-varying weights will allow us to better explore the dynamics of the financial sector and the changing nature of the relative positions of countries in the $GVAR$ system.

As for "global" variables, we select variables that proxy risk aversion sentiment in the global and regional financial markets including the VDAX implied volatility index ($vdax_t$), the spread between 3 month EURIBOR interbank offering rate and EONIA overnight risk free rate ($euribor - ois_t$), and the spread between Moody's BAA and

[3] We collect data from the "Consolidated Banking Statistics" section of the BIS website. We use "Foreign claims by nationality of reporting banks, immediate borrower basis" as the definition of the claim exposure of the banking sector of countries $i - j$ pair.

AAA corporate indices (baa_t).

We include monthly data from 2004M01 to 2014M09 (129 periods) for $r_{i,t}$, $seq_{i,t}$, $vdax_t$, $euribor - ois_t$, and baa_t. We include quarterly data from 2004Q1 to 2014Q3 (43 periods) for $y_{i,t}$ and $debt_{i,t}$, then convert them into monthly series using cubic spline interpolation. For sovereign CDS spreads $scds$, series are available for 13 countries except for Greece[4]. To represent the country-specific banking sector, we construct the sovereign banking sector equity returns seqs from the equity returns of commercial banks that are publicly listed on Country i's stock exchange markets, weighted by each firm's total assets each period. Table 4.10 reports the full definitions of variables and data sources.

Figure 4.1: **Cross-country Flows: Banking Sector versus Trade**
This figure reports the comparisons between cross-country exposure of the banking sector(left) and trade-flows(right). The bank exposure data is obtained from Bank of International Settlements website and the trade-flows data from OECD database. Note that the bank exposure data for Ireland is only available after 2006, and in our study we expand the 2006 values to previous periods.

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[4]On 9 March 2012 the Greece government announced its acceptance of the terms for its second round bail-out package including massive write-off of Greek debt from private investors. The International Swaps and Derivatives Association (ISDA) declared this a triggering credit event and subsequently Greece's sovereign CDS ceased trading with payouts to protection buyers after a CDS settlement auction.

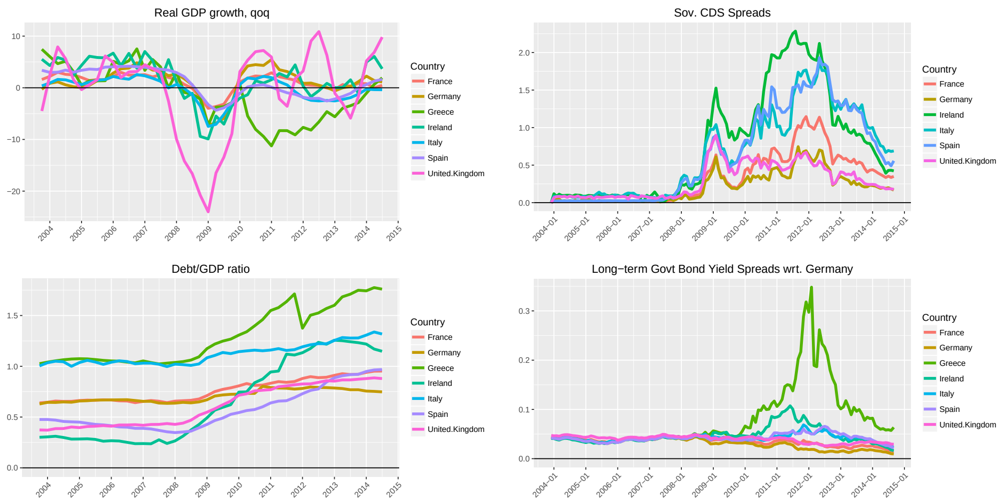

Figure 4.2: **Time-series Data description**

Figure 4.2 plots the time series evolutions in our sample[5]. The quarter-on-quarter real economies in the EU countries enjoyed relatively stable and moderate growth prior to the global financial crisis, and experienced different degrees of declines around 2008 (especially the UK) and 2011 (especially Greece). Germany's debt level remains roughly around the debt level criterion of the Maastricht treaty (60%) throughout the sample periods and its economy regained relatively higher level of growth compared to other peer countries. As shown from the figure, Greece and Italy are the two countries whose debt levels remained high throughout the sample periods. As for UK, the dramatic fluctuation of its economic growth was due to the fact that a large proportion of its economy is related to financial services and therefore its economic indicators are prone to macro-financial climate in the world. As for Greece, as the source of the Greek debt crisis, its government bond yield spreads with respect to Germany's climbed sharply during the debt crisis, and although it enjoyed the debt write-off from its second round bailout package on 2012, its debt level remained high and climbing whereas the economy went through a prolonged episode

[5]To be consistent with the literature, we use real GDP growth instead of quarter-on-quarter GDP growth.

of massive decline. The rest of the "distressed countries" all showed certain degrees of similarities of their economic characteristics: their debt levels were either high and/or climbing (especially Ireland before 2013), they went through economic declines during the two crises and their bond yields/sovereign CDS spreads with respect to Germany all climbed up rapidly during the sovereign debt crisis[6] as the market concern about the fiscal health and sustainability of the European Union rose but gradually calmed down in recent periods.

4.5 Empirical Results and Diagnostics

4.5.1 Country-specific $VARX^*$ Model

We specify each $VARX^*(p_i, q_i)$ model such as the lag order of its endogenous/exogenous variables and long-run relationships based on diagnostic tests so that our models satisfy the theoretical prerequisites of the $GVAR$ framework as discussed in Dees et al. (2007) and Chudik and Pesaran (2014). For stationarity conditions, we perform unit root tests based Augmented Dickey-Fuller tests and report standard ADF statistics as well as Weighted-Symmetric ADF statistics introduced by Park and Fuller (1995). The WS statistics, as discussed in Dees et al. (2007), exploit the time reversibility of stationary autoregressive processes in order to increase their power performance. The lag length in the unit root tests are based on Akaike Information Criterion (AIC). As the $GVAR$ model at most can accommodate integration up to order 1, we need to confirm that all of our variables are at most $I(1)$. For each variable, their levels with/without trend as well as first-differences are reported. As shown by the results of Tables 4.1 and 4.2, with a few exceptions, most variables show the presence of unit roots at level and all variables become stationary after first difference.

[6] Also in a smaller degree, during the financial crisis, as shown by their sovereign CDS spreads.

We then consider the specification of each country-specific model in order to fully explore the potential interactions that can be allowed in the system. Variable selection is done based on weak exogeneity test of Johansen (1992*b*) and persistence profile results. As our sample cover the periods of two economic crises, our primary interest is on the short-run dynamics of the model rather than the long-run relationships of the error-correction component. We select the lag length of the country-specific models based on AIC results and set the lag length of the endogenous and exogenous variables, p_i and q_i to be 2 and 1 for all countries. Using Johansen techniques on $VECM$ models, we found that there are co-integration ranks of 2 for Austria, Belgium, Denmark, Finland, ranks 0 for Germany and France. As for "distressed countries" group, we found ranks 1 for most countries except for Greece and Ireland. Considering the violent reactions in bond and CDS markets during crisis episodes in these countries, we restrict the ranks to 0 for these countries, as exploring the long-run structure using crisis observations would not yield correct result and this is not our primary interest of research.

Table 4.1: **Unit Root Test Results - Augmented Dicky Fuller Tests**

Table 4.1 reports the Augmented Dicky Fuller unit root test results for domestic and global variables used in the model. For each variable, results for level as well as first differenced versions are provided. The null hypothesis of the test indicate unit root. Test statistics being greater than critical values implies the presence of unit root.

Domestic Variables	Critical Value	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE
y (with trend)	-03.45	-02.05	-02.13	-01.17	-02.28	-02.83	-02.80	-01.95
y (no trend)	-02.89	-01.50	-01.40	-01.44	-02.57	-01.69	-01.48	-00.23
Δy	-02.89	-04.18	-03.98	-03.66	-03.77	-03.62	-03.75	-02.85
$debt$ (with trend)	-03.45	-01.76	-02.84	-02.33	-01.59	-01.77	-01.42	-02.11
$debt$ (no trend)	-02.89	-01.37	-01.07	-01.35	-00.07	00.53	-01.12	-00.03
$\Delta debt$	-02.89	-08.85	-08.63	-04.16	-06.29	-04.67	-04.76	-05.93
$scds$ (with trend)	-03.45	-01.84	-01.39	-02.98	-02.48	-01.58	-01.94	
$scds$ (no trend)	-02.89	-01.87	-01.53	-02.77	-02.15	-01.49	-01.80	
$\Delta scds$	-02.89	-05.41	-05.30	-07.54	-07.58	-07.11	-07.39	
r (with trend)	-03.45	-01.73	-00.96	-02.12	-01.99	-02.08	-02.41	-01.44
r (no trend)	-02.89	00.06	00.14	-00.72	-00.48	-00.58	-00.66	-01.48
Δr	-02.89	-09.44	-10.02	-05.63	-05.64	-08.03	-05.58	-06.29
seq (with trend)	-03.45	-02.53	-02.02	-01.74	-01.48	-02.07	-01.85	-02.14
seq (no trend)	-02.89	-00.72	-01.59	-01.62	-00.15	-01.51	-01.65	00.71
Δseq	-02.89	-04.01	-05.10	-06.45	-08.41	-07.51	-08.24	-07.90

Domestic Variables	Critical Value	IRELAND	ITALY	NETHERLANDS	PORTUGAL	SPAIN	SWEDEN	UK
y (with trend)	-03.45	-02.41	-02.57	-01.60	-01.73	-02.63	-01.34	-01.02
y (no trend)	-02.89	-02.57	-01.32	-02.33	-01.08	-02.70	-01.62	-01.46
Δy	-02.89	-04.43	-03.23	-02.92	-03.53	-02.74	-03.60	-03.64
$debt$ (with trend)	-03.45	-01.99	-01.83	-02.12	-01.38	-02.22	-00.96	-01.92
$debt$ (no trend)	-02.89	-00.58	00.61	-00.51	01.30	00.17	-02.33	-01.32
$\Delta debt$	-02.89	-03.67	-06.77	-04.16	-04.26	-02.45	-07.96	-02.30
$scds$ (with trend)	-03.45	-01.28	-02.13	-02.51	-01.61	-00.45	-03.22	-01.88
$scds$ (no trend)	-02.89	-01.56	-01.46	-02.17	-01.46	-01.21	-02.91	-01.95
$\Delta scds$	-02.89	-04.30	-05.65	-06.00	-03.51	-05.28	-10.57	-05.75
r (with trend)	-03.45	-00.74	-01.41	-01.99	-01.16	-00.71	-03.14	-02.61
r (no trend)	-02.89	-01.09	-01.65	-00.45	-01.48	-01.16	-01.61	-01.33
Δr	-02.89	-07.81	-08.65	-05.65	-06.36	-07.71	-05.21	-06.27
seq (with trend)	-03.45	-01.71	-02.40	-02.42	-02.15	-01.97	-01.68	-01.54
seq (no trend)	-02.89	-00.67	-01.04	-01.68	-00.81	-01.48	-01.65	-01.12
Δseq	-02.89	-06.42	-03.89	-04.06	-06.83	-08.35	-07.16	-06.08

Global Variables	Critical Value	Statistic
$vdax$ (with trend)	-03.45	-02.67
$vdax$ (no trend)	-02.89	-02.65
$\Delta vdax$	-02.89	-09.89
$euribor - ois$ (with trend)	-03.45	-02.25
$euribor - ois$ (no trend)	-02.89	-01.24
$\Delta euribor - ois$	-02.89	-03.79
baa (with trend)	-03.45	-02.44
baa (no trend)	-02.89	-02.51
Δbaa	-02.89	-06.25

Table 4.2: **Unit Root Test Results - Weighted-Symmetric Augmented Dicky Fuller Tests**

Table 4.2 reports the Weighted-Symmetric Augmented Dicky Fuller unit root test results for domestic and global variables used in the model. For each variable, results for level as well as first differenced versions are provided. The null hypothesis of the test indicate unit root. Test statistics being greater than critical values implies the presence of unit root.

Domestic Variables	Critical Value	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE
y (with trend)	-03.24	-01.78	-00.99	-01.32	-01.53	-02.38	-03.00	-00.94
y (no trend)	-02.55	00.30	01.46	-01.66	-01.13	00.06	-00.78	-00.83
Δy	-02.55	-04.22	-03.69	-03.70	-03.91	-03.72	-03.96	-02.99
$debt$ (with trend)	-03.24	-02.04	-01.61	-01.42	-00.84	-01.02	-01.66	-01.68
$debt$ (no trend)	-02.55	-01.04	-01.29	-01.35	-00.70	00.25	-00.86	-00.23
$\Delta debt$	-02.55	-09.07	-09.12	-04.29	-06.53	-04.87	-04.97	-06.13
$scds$ (with trend)	-03.24	-02.11	-01.75	-03.18	-02.71	-01.82	-02.17	
$scds$ (no trend)	-02.55	-01.91	-01.57	-02.83	-02.21	-01.51	-01.89	
$\Delta scds$	-02.55	-05.62	-05.51	-07.73	-07.73	-07.26	-07.55	
r (with trend)	-03.24	-01.93	-01.29	-02.35	-02.13	-02.28	-02.54	-01.74
r (no trend)	-02.55	-00.08	-00.11	-00.61	-00.55	-00.59	-00.60	-01.72
Δr	-02.55	-09.54	-10.14	-05.80	-05.81	-08.14	-05.76	-06.50
seq (with trend)	-03.24	-01.84	-02.10	-01.81	-01.07	-02.02	-02.08	-00.81
seq (no trend)	-02.55	-01.12	-01.88	-01.94	-00.72	-01.80	-01.84	00.10
Δseq	-02.55	-04.15	-05.27	-06.60	-08.53	-07.67	-08.37	-08.05

Domestic Variables	Critical Value	IRELAND	ITALY	NETHERLANDS	PORTUGAL	SPAIN	SWEDEN	UK
y (with trend)	-03.24	-01.67	-01.89	-01.05	-01.10	-01.57	-01.54	-01.29
y (no trend)	-02.55	-01.26	-01.63	-00.27	-01.21	-01.31	-01.93	-01.72
Δy	-02.55	-04.62	-03.37	-03.11	-03.53	-02.90	-03.60	-03.73
$debt$ (with trend)	-03.24	-01.25	-01.36	-01.64	-00.73	-01.03	-00.93	-01.63
$debt$ (no trend)	-02.55	-00.82	00.12	-00.88	00.85	-00.55	-00.36	-01.17
$\Delta debt$	-02.55	-03.85	-06.89	-04.35	-04.39	-02.56	-08.17	-02.56
$scds$ (with trend)	-03.24	-01.65	-02.36	-02.72	-01.84	-00.79	-03.42	-02.20
$scds$ (no trend)	-02.55	-01.64	-01.43	-02.17	-01.52	-01.16	-02.94	-01.96
$\Delta scds$	-02.55	-04.48	-05.86	-06.21	-03.72	-05.46	-10.75	-05.95
r (with trend)	-03.24	-01.14	-01.72	-02.15	-01.48	-01.04	-03.33	-02.77
r (no trend)	-02.55	-01.38	-01.88	-00.48	-01.72	-01.42	-01.07	-01.31
Δr	-02.55	-07.95	-08.77	-05.82	-06.50	-07.85	-05.38	-06.39
seq (with trend)	-03.24	-01.38	-02.13	-02.48	-01.99	-02.02	-01.94	-01.73
seq (no trend)	-02.55	-00.73	-01.30	-01.92	-01.01	-01.67	-01.85	-00.98
Δseq	-02.55	-06.58	-04.09	-04.25	-06.96	-08.51	-07.31	-06.22

Global Variables	Critical Value	Statistic
$vdax$ (with trend)	-03.45	-02.82
$vdax$ (no trend)	-02.89	-02.85
$\Delta vdax$	-02.89	-10.05
$euribor - ois$ (with trend)	-03.45	-02.07
$euribor - ois$ (no trend)	-02.89	-01.58
$\Delta euribor - ois$	-02.89	-03.98
baa (with trend)	-03.45	-02.64
baa (no trend)	-02.89	-02.66
Δbaa	-02.89	-06.33

Table 4.3: **Model Specifications**

Country	p_i	q_i	Coint. Ranks	Variable Specifications										
				y	$debt$	$scds$	r	seq	$scds^*$	r^*	seq^*	$vdax$	$euribor-ois$	baa
AUSTRIA	2	1	2	X	X	X	X	X	X	X	X	X	X	X
BELGIUM	2	1	2	X	X	X	X	X	X	X	X	X	X	X
DENMARK	2	1	2	X	X	X	X	X	X	X	X	X	X	X
FINLAND	2	1	2	X	X	X	X	X	X	X	X	X	X	X
FRANCE	2	1	0	X	X	X	X	X	X	X	X	X	X	X
GERMANY	2	1	0	X	X	X	X	X	X	X	X	X	X	X
GREECE	2	1	0	X	X	-	X	X	X	X	X	X	X	X
IRELAND	2	1	0	X	X	X	X	X	X	X	X	X	X	X
ITALY	2	1	0	X	X	X	X	X	X	X	X	X	X	X
NETHERLANDS	2	1	1	X	X	X	X	X	X	X	X	X	X	X
PORTUGAL	2	1	0	X	X	X	X	X	X	X	X	X	X	X
SPAIN	2	1	0	X	X	X	X	X	X	X	X	X	X	X
SWEDEN	2	1	2	X	X	X	X	X	X	X	X	X	X	X
UK	2	1	2	X	X	X	X	X	X	X	X	X	X	X

4.5.2 Global Model: Properties of the $GVAR$

For the $GVAR$ model to be stable, there are two conditions that needs to be satisfied: the eigenvalues of the matrix **F** from (4.7) would be either inside the unit circle or on the unit circle in the presence of $I(1)$ variables, and the persistence profiles derived from a VMA (vector moving average) form of the model would converge to zero over the time horizons. There are 144 eigenvalues for matrix **F**[7]. For the model to be stable, it requires at least $72 - 15 = 57$ eigenvalues to lie on the unit circle given that we have 72 endogenous variables and 15 ranks (cointegrating relationships) in the global model. Among the 144 eigenvalues of matrix **F** there are 57 that lies on the unit circle and 87 inside the unit circle, which confirms the stationarity condition of matrix **F**. We then examine the long-run properties of the model by looking at the persistence profiles proposed by (Pesaran and Shin, 1996) of the $GVAR$ model. The persistence profiles are derived using moving average representation of the $VARX^*$ structure and

[7] Matrix **F** is a $kp \times 1$ matrix, where k is the number of endogenous variables and p is the highest value of p_is in each country-specific $VARX^*(p_i, q_i)$ structure. In our case, we have 72 endogenous variables ($k = 72$) and the highest order of lags is 2 ($p = 2$).

compare the responses of the step-n error term with the responses at step-0 given a shock of unit one at step-0. This technique provides information on the speed with which the cointegrating relationships of the country-specific models converge to their equilibrium states. In the case of a stable system where the cointegrating vectors are stationary, the profiles would converge to zero while in the case of an unstable system they might behave in an explosive way. Therefore if the *GVAR* model is correctly specified, we should observe the convergence of shocks within the time horizon. As shown from Figure 4.3, we show that the responses would return to 0 after about 10 periods, which confirms that our model is stable.

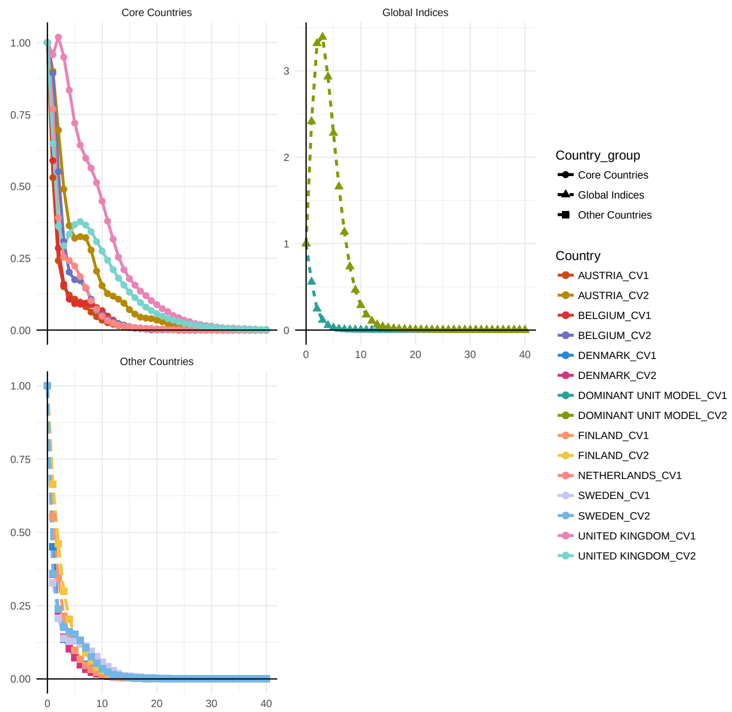

Figure 4.3: **Persistence Profile**

The pairwise cross-section correlations (Table 4.4) allow us to examine whether incorporating foreign effects as good proxies of unobserved common factors. One of the key assumptions of the *GVAR* framework is the "idiosyncratic" shocks to country-specific models should be "weakly correlated" so that the foreign variables incorporated in to the models would be weakly exogenous. For each variable, the pairwise cross-section correlation is computed by averaging the correlations of the specific variable in the specific country against the equivalent variable in other countries. As shown from Table 4.4, the levels and the first differences of the variables show high levels of correlations whereas the correlations of the residuals drop significantly due to the incorporation of foreign effects in the country-specific model. The different degrees of remaining effects, as Di Mauro and Pesaran (2013) notes, might reflect policy and spillover effects. From another perspective, Table 4.5 reports the contemporaneous effects of changes of domestic variables due to changes in their foreign counterparts. We report the estimated coefficients with Newey-West type HAC standard errors and t-values, for r, $scds$, and seq. The results show that for the sovereign risk indicators in the "distressed countries" (Greece, Portugal, Spain), the one unit change in their foreign counterparts would often produce more than one unit responses, giving clear evidence that these countries are prone to external shocks.

Table 4.4: **Average Pairwise Cross-section Correlations**
Table 4.4 reports the pairwise cross-section correlations of the domestic variables (in level as well as in first differences), and the pairwise cross-section correlations of the model residuals. The pairwise cross-section correlation of a domestic variable is the correlation between the domestic variable of one country with the same domestic variables of another country, which will then be averaged across all countries. The purpose of calculating the cross-section correlations of variables and residuals is to show the effectiveness of reducing cross-sectional dependence of a group of variables across different countries by including weighted foreign variables as proxies of common factors.

		Level Coefs	First Differences	$VECMX^{*}$ Residuals			Level Coefs	First Differences	$VECMX^{*}$ Residuals
y	AUSTRIA	0.28	0.43	0.10	r	AUSTRIA	0.54	0.53	0.18
	BELGIUM	0.27	0.62	0.20		BELGIUM	0.59	0.53	0.03
	DENMARK	0.08	0.49	0.23		DENMARK	0.48	0.48	0.04
	FINLAND	0.50	0.58	0.11		FINLAND	0.50	0.57	0.02
	FRANCE	0.31	0.60	0.25		FRANCE	0.55	0.60	0.25
	GERMANY	0.29	0.62	0.28		GERMANY	0.47	0.56	0.22
	GREECE	0.08	0.28	0.06		GREECE	–0.12	0.06	0.02
	IRELAND	0.48	0.28	-0.01		IRELAND	0.22	0.39	-0.02
	ITALY	0.28	0.64	0.26		ITALY	0.27	0.38	-0.03
	NETHERLANDS	0.35	0.53	0.08		NETHERLANDS	0.50	0.58	0.00
	PORTUGAL	0.26	0.49	0.15		PORTUGAL	–0.02	0.23	0.00
	SPAIN	0.43	0.53	0.06		SPAIN	0.14	0.42	0.01
	SWEDEN	0.18	0.50	0.21		SWEDEN	0.42	0.50	-0.04
	UK	0.11	0.49	0.23		UK	0.42	0.43	0.12
$debt$	AUSTRIA	0.74	0.19	0.02	seq	AUSTRIA	0.79	0.51	0.05
	BELGIUM	0.76	0.23	-0.05		BELGIUM	0.81	0.60	0.05
	DENMARK	0.63	0.31	0.08		DENMARK	0.77	0.56	0.04
	FINLAND	0.80	0.14	-0.04		FINLAND	0.54	0.19	-0.02
	FRANCE	0.80	0.31	0.08		FRANCE	0.85	0.67	0.20
	GERMANY	0.76	0.16	0.05		GERMANY	0.80	0.60	0.14
	GREECE	0.79	0.09	-0.02		GREECE	0.70	0.50	0.08
	IRELAND	0.80	0.20	-0.11		IRELAND	0.81	0.55	0.12
	ITALY	0.80	0.27	0.04		ITALY	0.85	0.66	0.17
	NETHERLANDS	0.81	0.28	0.12		NETHERLANDS	0.83	0.62	-0.01
	PORTUGAL	0.78	0.18	0.01		PORTUGAL	0.82	0.50	0.10
	SPAIN	0.80	0.32	0.02		SPAIN	0.85	0.62	0.12
	SWEDEN	-0.42	0.00	-0.02		SWEDEN	0.28	0.57	0.05
	UK	0.78	0.26	-0.03		UK	0.81	0.58	0.13
$scds$	AUSTRIA	0.88	0.68	0.01					
	BELGIUM	0.89	0.68	0.00					
	DENMARK	0.81	0.46	0.02					
	FINLAND	0.89	0.65	0.13					
	FRANCE	0.89	0.71	0.23					
	GERMANY	0.91	0.67	0.21					
	GREECE								
	IRELAND	0.87	0.58	0.00					
	ITALY	0.86	0.65	0.00					
	NETHERLANDS	0.90	0.69	0.00					
	PORTUGAL	0.82	0.47	0.11					
	SPAIN	0.85	0.62	0.04					
	SWEDEN	0.63	0.32	-0.07					
	UK	0.83	0.65	0.16					

Table 4.5: **Contemporaneous Effects**
Table 4.5 reports the contemporaneous effects of foreign variables on the counterpart domestic variables, with Newey-West heteroscedasticity-robust standard errors and t-statistics. Coefficient value indicates reaction of domestic variables due to changes of counterpart foreign variables.

	countries	r	scds	seq	countries	r	scds	seq
Coefficient	AUSTRIA	1.12	1.07	0.39	IRELAND	1.37	1.13	0.63
(se)		(0.10)	(0.12)	(0.08)		(0.30)	(0.21)	(0.31)
t-ratio		*3.20*	*8.61*	*5.12*		*4.54*	*5.45*	*2.01*
Coefficient	BELGIUM	1.10	1.10	0.82	ITALY	0.97	1.09	0.37
(se)		(0.14)	(0.09)	(0.14)		(0.16)	(0.19)	(0.24)
t-ratio		*8.05*	*12.19*	*5.80*		*5.96*	*5.83*	*1.57*
Coefficient	DENMARK	1.21	0.76	0.82	NETHERLANDS	0.90	0.69	1.02
(se)		(0.09)	(0.31)	(0.15)		(0.07)	(0.07)	(0.18)
t-ratio		*13.17*	*2.42*	*5.41*		*12.23*	*9.75*	*5.75*
Coefficient	FINLAND	0.88	0.30	0.00	PORTUGAL	1.25	0.64	0.38
(se)		(0.04)	(0.09)	(0.07)		(0.16)	(0.12)	(0.14)
t-ratio		*23.31*	*3.34*	*0.03*		*7.82*	*1.50*	*2.72*
Coefficient	FRANCE	1.13	0.66	0.21	SPAIN	0.99	1.19	0.50
(se)		(0.05)	(0.25)	(0.35)		(0.13)	(0.18)	(0.10)
t-ratio		*5.38*	*3.20*	*4.08*		*7.48*	*6.70*	*4.78*
Coefficient	GERMANY	0.65	1.20	1.05	SWEDEN	0.88	0.74	0.73
(se)		(0.12)	(0.15)	(0.24)		(0.05)	(0.25)	(0.12)
t-ratio		*10.05*	*3.20*	*5.80*		*19.59*	*2.92*	*5.98*
Coefficient	GREECE	1.48		0.79	UNITED KINGDOM	1.09	1.06	0.81
(se)		(1.17)		(0.25)		(0.15)	(0.20)	(0.10)
t-ratio		*1.27*		*3.15*		*4.38*	*2.20*	*4.58*

Weak Exogeneity Test

Lastly, We report the formal results for weak exogeneity tests. Following the concept by Johansen (1992*a*), the weak exogeneity assumption of the $VECMX$ models implies that there should be no long run feedback from $\mathbf{x}_{it}$ to $\mathbf{x}^*_{it}$, so that the α coefficients of $\mathbf{x}^*_{it}$ could be treated as zero, meaning that in the case of $GVAR$, the effects of the foreign variables remain in the short-run and would not have long-run effects. Formally, the test model for the weak exogeneity of $\mathbf{x}^*_{it}$ is constructed as:

$$\Delta x^*_{it,l} = a_{il} + \sum_{j=1}^{r_i} \delta_{ij,l} E\hat{C}M_{ij,t-1} + \sum_{s=1}^{p^i_*} \phi'_{is,l}\delta\mathbf{x}_{i,t-s} + \sum_{s=1}^{q^i_*} \psi'_{is,l}\delta\tilde{\mathbf{X}}^*_{i,t-s} + \eta_{it,l} \tag{4.10}$$

Then the weak exogeneity test is an $F - test$ of the joint significance of the coefficients $\delta_{ij,l}$ of the ECM components when regressing the vector of foreign variables to the ECM components, and if the coefficients are jointly insignificant we confirm the weak exogeneity of the foreign variables. Table 4.6 reports the test results and we confirm weak exogeneity for most of the foreign variables in out model specifications.

Table 4.6: **Weak Exogeneity Tests**
Table 4.6 reports the results of weak exogeneity tests for foreign variables and global variables. The null hypothesis of the test indicates weak exogeneity of the variables (treating their adjustment coefficients as zero in the error-correction component). Test statistics being lower than critical values implies weak exogeneity.

Country	Critical Value	$scds^*$	r^*	seq^*	$vdax$	$euribor - ois$	baa
AUSTRIA	3.08	0.79	0.88	0.37	1.45	3.12	0.25
BELGIUM	2.69	0.74	1.02	2.21	0.07	1.09	0.64
DENMARK	3.08	0.28	0.84	1.13	3.62	1.15	1.96
FINLAND	3.08	2.03	0.65	1.22	0.22	0.12	0.34
FRANCE	3.93	0.47	0.70	0.94	0.68	0.23	0.91
GERMANY	3.08	0.54	1.01	0.65	1.05	0.28	0.26
GREECE	3.08	1.13	1.18	0.60	1.14	0.32	0.49
IRELAND	3.08	0.69	0.48	0.72	0.46	1.16	0.57
ITALY	3.93	0.71	0.67	0.62	0.61	0.93	0.47
NETHERLANDS	3.93	0.22	0.01	0.24	1.08	0.11	0.01
PORTUGAL	3.93	1.06	0.98	0.73	1.09	1.20	0.54
SPAIN	3.08	0.27	0.37	0.66	0.87	1.02	1.17
SWEDEN	3.08	0.01	0.39	0.45	0.87	1.20	2.63
UK	3.08	1.16	0.57	0.94	0.33	0.19	1.39

4.6 Dynamic Analysis

In order to investigate the dynamic effects of sovereign distress in our study, we conduct dynamic analysis based on various scenarios. We use generalised impulse response functions ($GIRF$s) to investigate how an unexpected shock of one standard deviation from the variables of interest in specific countries can influence other variables and other countries. We then employ network plots based on the $GIRF$s to visually depict the interconnectedness relationship of the countries in the sample. Lastly We use generalised forecast error variance decompositions ($GFEVD$s) to investigate the geographical origins of shocks to various variables of interest[8]. Our

[8] Utilising generalised IRF and $FEVD$ techniques allows us to avoid the problem of choosing orthogonal variable orderings which need to be consistent with theoretical considerations or are otherwise widely accepted. Choosing orthogonal identifications are particularly difficult in a multi-

variables of interest will focus on the three potential channels of contagion, *r*, *scds*, and *seq*. The dynamic simulation results are generated from 1000 bootstrap repetitions over the horizon of 40 periods (three years).

4.6.1 Generalised Impulse Responses

In terms of generating generalised impulse responses to the variables of interest, we discuss three scenarios: 1. Increase in the fiscal distress represented by one standard error positive shock to the national debt/GDP ratio; 2. Slowdown in economic output represented by one standard error negative shock to the real GDP growth; 3. Downturn in market sentiment represented by one standard error positive shock to the three global variables: market volatility (*vdax*), interbank lending rate (*euribor*), and credit risk spread (*baa*).

Increase in Government Debt

Tables 4.4, 4.5 and 4.6 report the impulse response results from a $+1\,se$ shock to *debt*. Comparing the responses from both indicators of sovereign credit risk, we find that sovereign CDS spreads *scds* is more responsive to shocks in national debt level than sovereign bond yields *r*. The sovereign bond yields of Greece has visible responses to national debt shocks, especially in the case of a one standard error positive shock to its domestic debt level, which results in 1% increase in the bond yields. In the case of sovereign CDS spreads, positive shocks to debt will trigger roughly 1% increase in CDS spreads in most of the cases. We can also see that domestic shocks can be expected to have greater responses in domestic variables than cross-border transmissions. In the case of responses from the banking sector, shocks from Germany, Italy and Ireland have the greatest impact to the banking sectors in all countries, for example a positive

country high-dimensional setting.

shock to national debt level will result in 1% loss in the banking sectors of Greece and Italy, and a positive shock to German debt level will result in losses in all countries by various degrees. The banking sector of Ireland is also found to be sensitive to sovereign debt changes as shocks in the German and UK debt levels result in 2% and 4% losses in the Irish banking sector respectively.

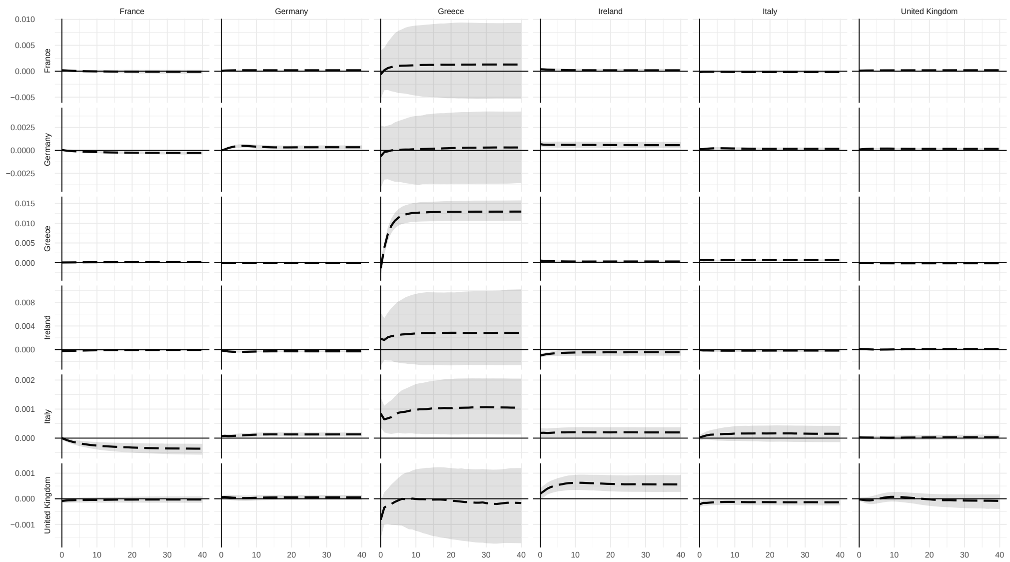

Figure 4.4: **GIRFs: +1 se shock from debt to sovereign bond yields**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

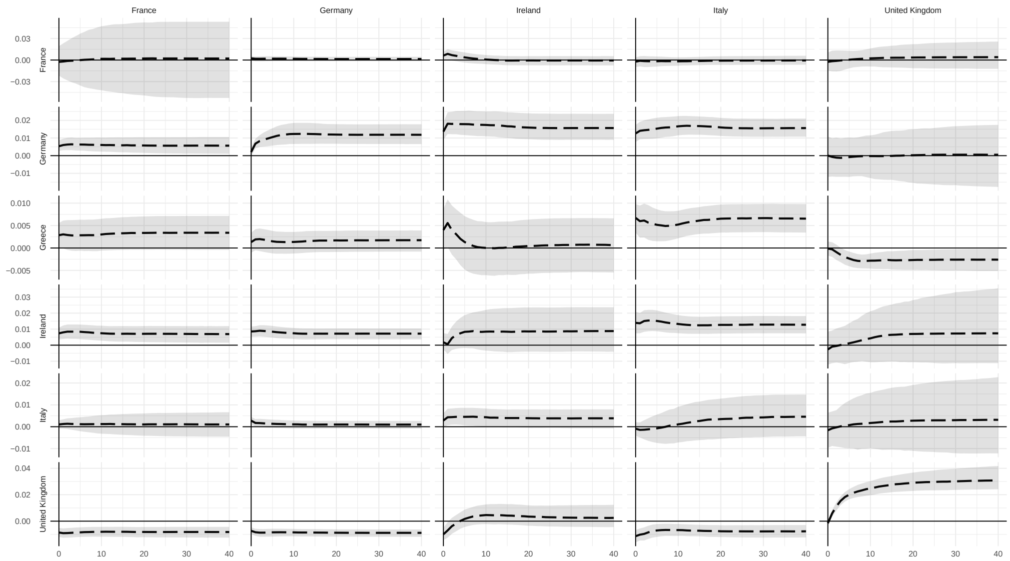

Figure 4.5: **GIRFs: +1 se shock from debt to sovereign CDS spreads**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

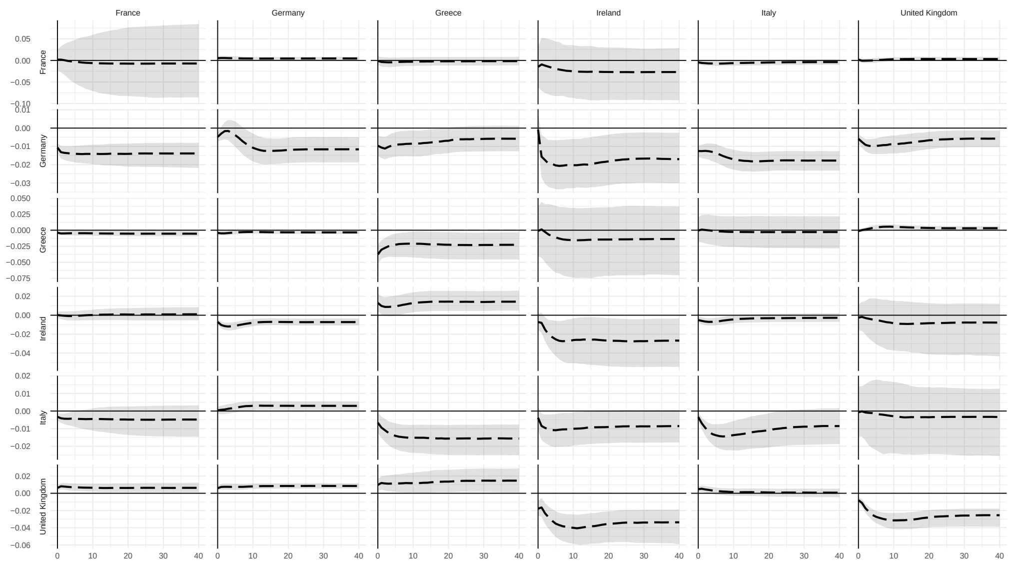

Figure 4.6: **GIRFs: +1 se shock from debt to sovereign banking-sector equity returns**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

As shown from the $GIRF$ figures, there exist heterogenous responses for countries/variables to shocks which will be difficult to summarise. In order to present the impact of shocks in a clear view, we construct network plots to illustrate the overall responses from *GIRF*s and to show the relative proximity of the countries/variables. Each of the nodes in the network plots represents a country-variable that transmits/receives the risk spillovers, with the width of the edges represents the mean average of the responses. The plots are drawn with the Fruchterman-Reigngold force-directed layout, which calculates the coordinates of the nodes based on the numbers of in/out links as well as the strength of the links. If there is a strong connection between two country-variables they will be placed close to each other when accounting for influences from other neighbours.

Figures 4.7, 4.8 and 4.9 show the summarised network plots of the one positive standard error shock from *debt* to *r*, *scds* and *seq*. We label the spillover effects from Greece, Ireland, Italy, Portugal and Spain, as well as Germany and France using distinct colours. There is a strong spillover effects from Germany to others countries, regardless of whether they are in distress or not. Portugal (all figures), Ireland (Figure 4.8) and Italy (Figure 4.9) are also shown to be strong originators of risk spillovers in different markets. Comparatively, there is weak evidence regarding spillover effects from Greece, which is more regarded as a receptor of spillovers in all three of the summarised network plots. In addition, UK is also mostly a receptor of spillovers, especially in the case of its banking sector in Figure 4.9, which implies a strong foreign sovereign risk influence to the UK banking sector and an undeniable source of systemic instability to the financial system.

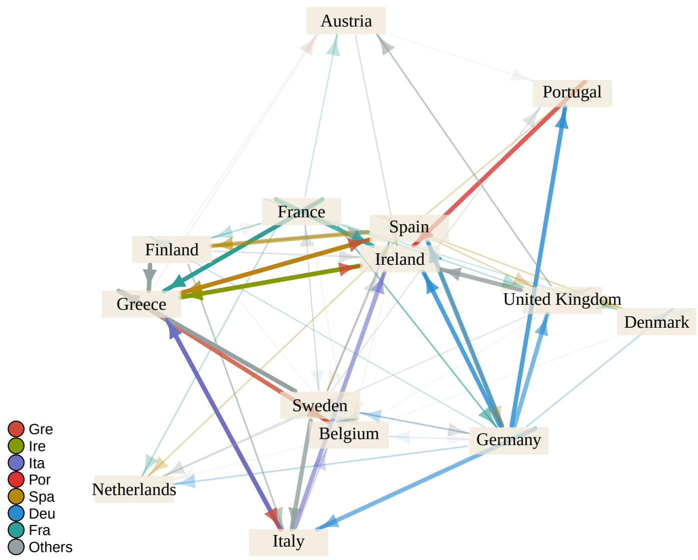

Figure 4.7: **GIRFs network: +1 se shock from debt to sovereign bond yields**

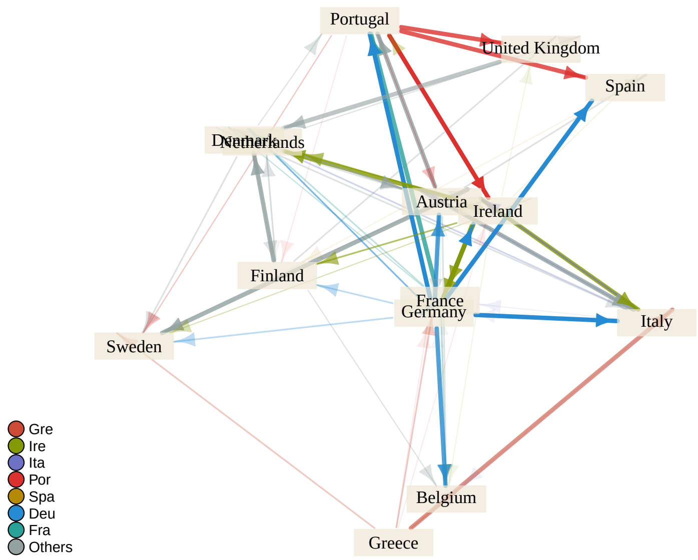

Figure 4.8: **GIRFs network: +1 se shock from debt to sovereign CDS**

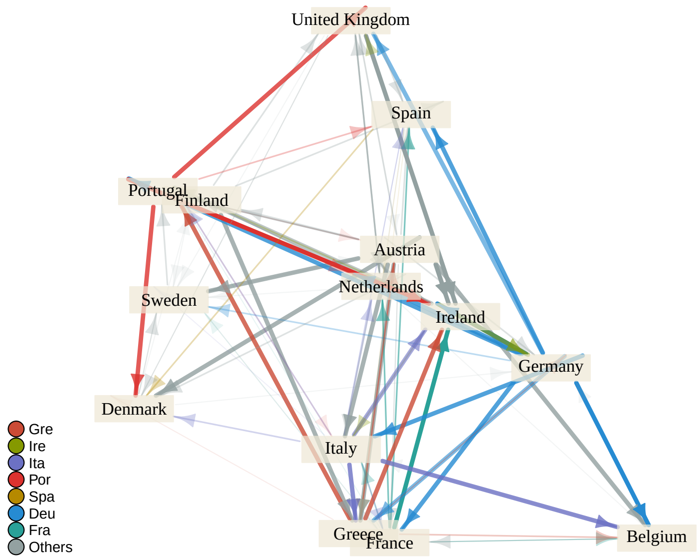

Figure 4.9: **GIRFs network: +1 se shock from debt to sovereign banking-sector equity returns**

Slow Down in GDP Growth

We then consider the scenario of a one standard error negative shock to GDP growth as an alternative scenario of a macroeconomic shock. Comparing with previous results in shocks to *debt* in Figure 4.10, most of the findings regarding the responses from *r*, *scds* and *seq* still hold. One of the exceptions is that there is a 0.1% increase in the sovereign bond yields of France following the shock to its GDP growth. In the case of *scds* in Figure 4.11, it is less sensitive to shocks in GDP growth and shocks to national debt level, with the exceptions of the shocks from Ireland to Ireland, from UK to Ireland, and from Germany to UK. In the case of *seq* in Figure 4.12, the responses from banking sector equity returns is greater from shocks of economic slowdowns than from debt level changes in Figure 4.5.

In the summarised network plots of Figures 4.13, 4.14 and 4.15, we find that there are more pair-specific heterogeneity and the overall spillover relationships are less clear-cut than previous results in shocks to *debt*. Nevertheless, we still observe the strong risk spillover effects from Germany and Portugal being visible. We also record minor spillover effects from economic slowdowns in Greece to the sovereign default spreads in other countries in Figure 4.14. In addition, there are also strong spillover effects from France to the banking sectors of other countries in Figure 4.15.

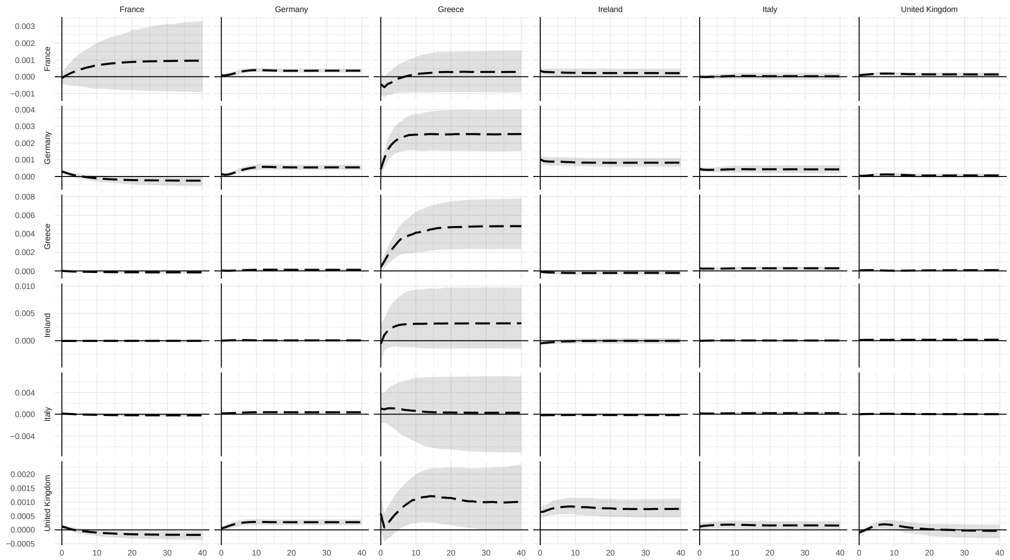

Figure 4.10: **GIRFs: -1 se shock from GDP growth to sovereign bond yields**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

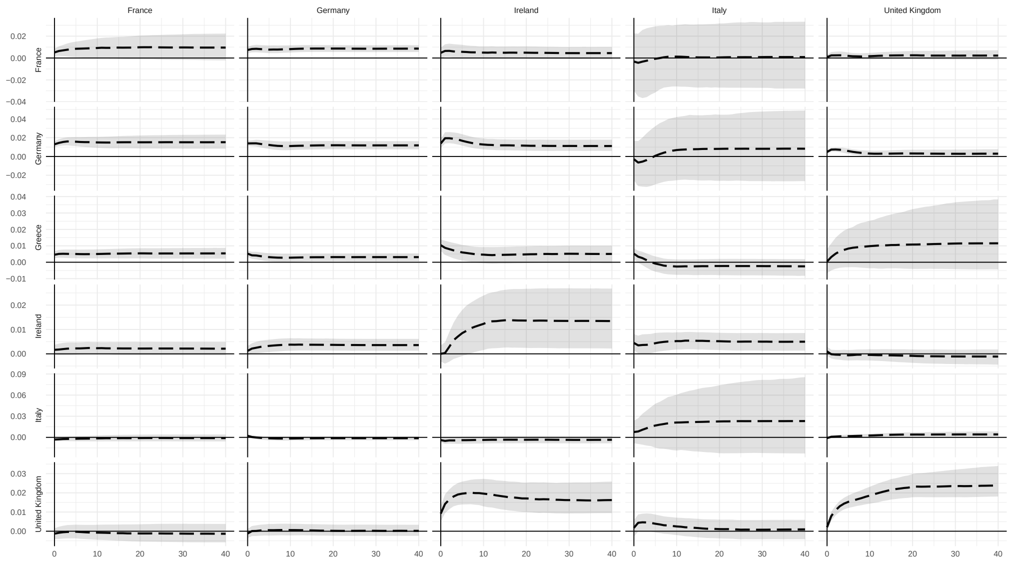

Figure 4.11: **GIRFs: -1 se shock from GDP growth to sovereign CDS spreads**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

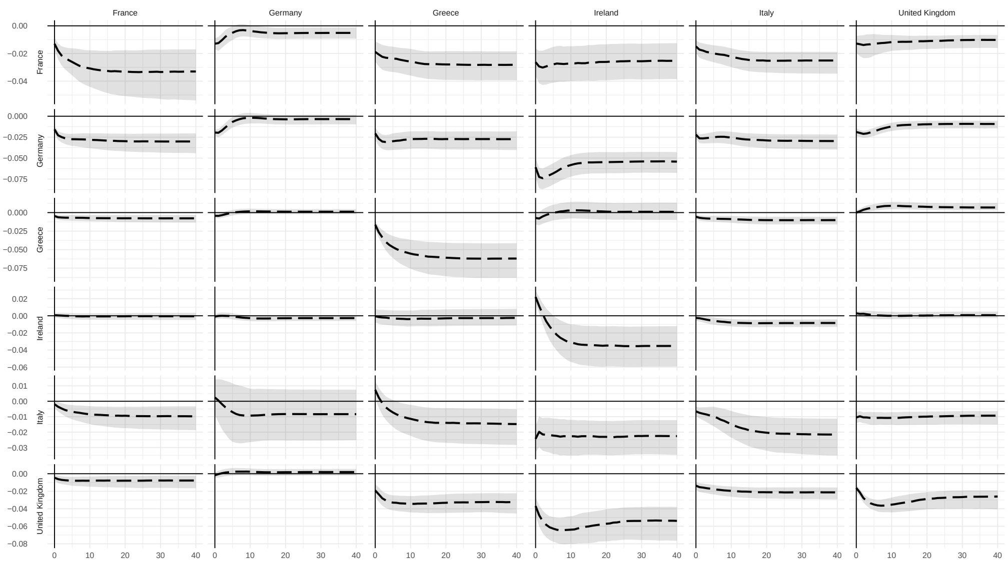

Figure 4.12: **GIRFs: -1 se shock from GDP growth to sovereign banking-sector equity returns**
The impulse responses of a (X, Y) pair, where X is the country/variable from which the shock is originated, and Y is the country/variable responding to the shock in X.

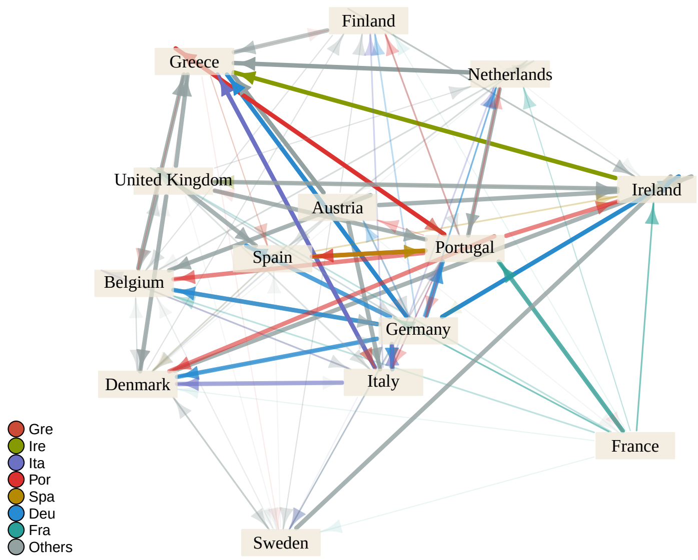

Figure 4.13: **GIRFs network: -1 se shock from GDP growth to sovereign bond yields**

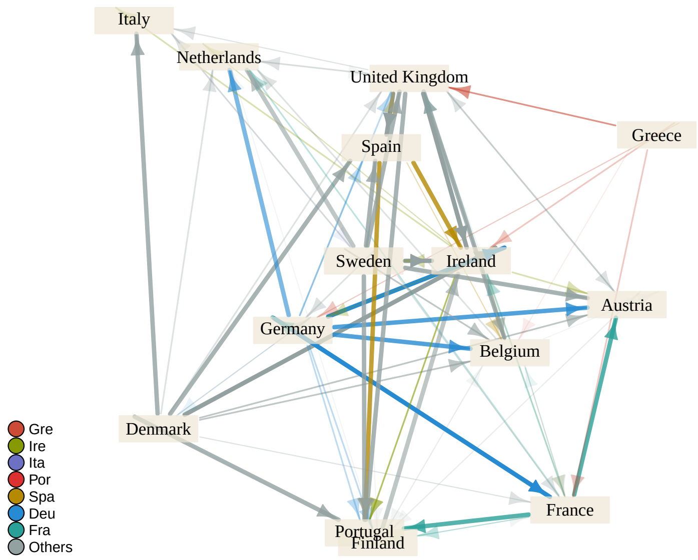

Figure 4.14: **GIRFs network: -1 se shock from GDP growth to sovereign CDS**

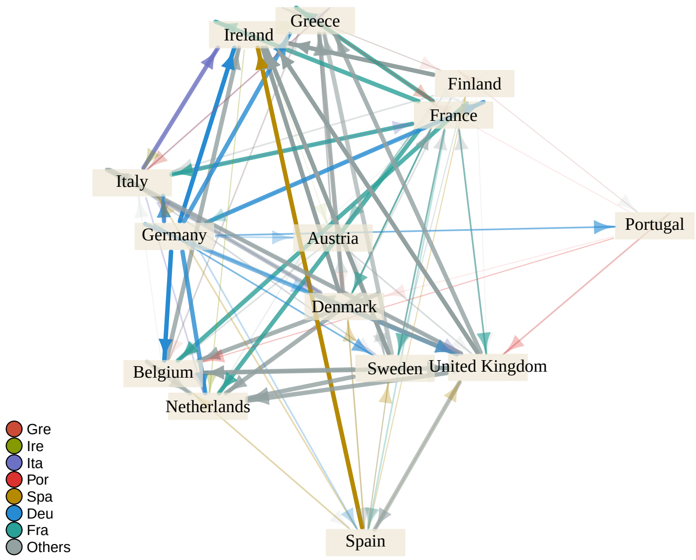

Figure 4.15: **GIRFs network: -1 se shock from GDP growth to sovereign banking-sector equity returns**

Downturn in Market Risk Climate

We then examine the responses of variables from shocks originated from global indices representing global financial risk sentiment. *baa* is the spread between Moody's BAA index and AAA index which is used as a proxy for credit risk in the financial market (Adrian and Brunnermeier, 2011; Hautsch et al., 2012), $euribor - ois$ is the spreads between short-term interbank lending rate and overnight risk free rate which proxies the liquidity premium in the market (Caporale and Girardi, 2013), and *vdax* is the volatility index of the German stock index which proxies the volatility in asset returns in the stock market (Sharifova, 2012). Figure 4.16 illustrates the relative responses of *r*, *scds*, and *seq* from one positive standard deviation shock of global market indices (representing worsening market conditions). We find that sovereign bond yields do not respond to the financial market shocks, whereas there are short term increases in sovereign CDS spreads which recover in 10 periods, especially for the *scds* of Italy and Ireland. In terms of responses from banking sector equity returns, they are also affected negatively in the short term by the shocks to global financial indices in various degrees. Our results show that market volatility and credit risk create more impact to banking sector than liquidity risk. Given the fact that most of the countries we examine are Eurozone countries, this finding shows that the market distress during the Eurozone sovereign crisis is more dominated by the credit risk and market volatility and less by the liquidity risk component.

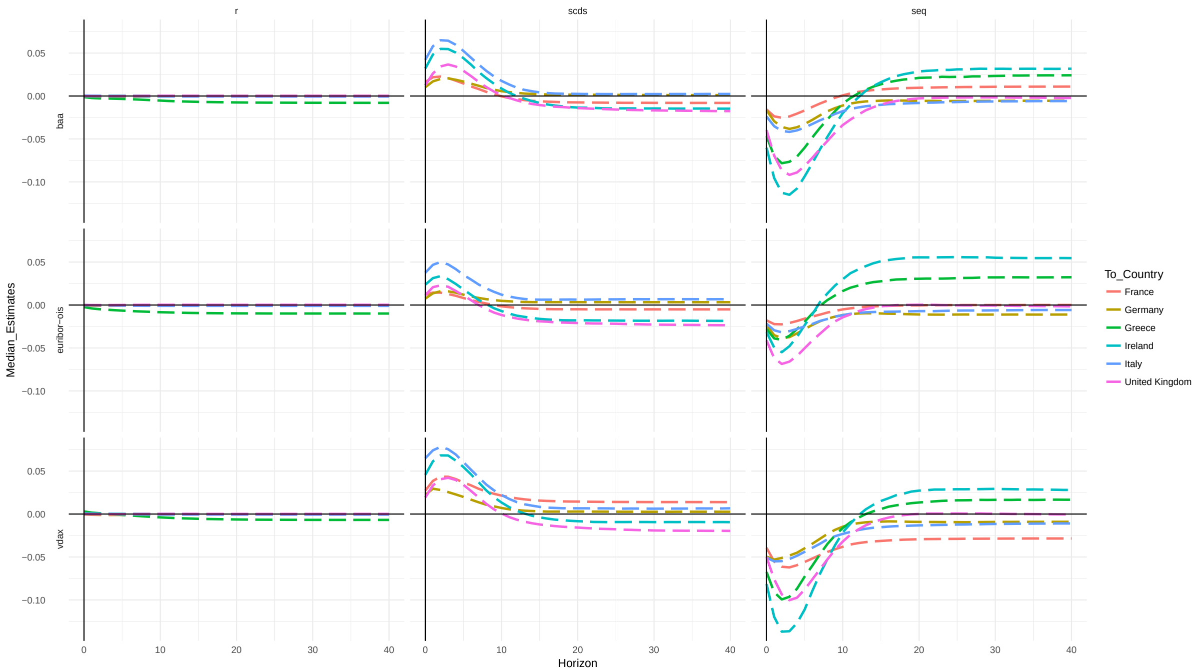

Figure 4.16: **GIRFs: +1 se shock from global indices to sovereign bond yields, CDS spreads, and banking-sector equity returns**
Variables on the vertical axis are variables that shocks originate from, whereas variables on the horizontal axis are variables where shocks are received.

4.6.2 Generalised Forecast Error Variance Decompositions

From another perspective, we consider the origins of shocks to *r*, *scds*, and *seq* and the contributions from domestic/foreign variables using generalised forecast error variance decompositions. Tables 4.7, 4.8, and 4.9 report GFEVD results and Figures 4.17, 4.18, and 4.19 report graphically the relative contribution of variables over the horizons. We group the variance decompositions into "self", "core", "distressed", and "global" groups containing the summed values of the variables in the groups.

In terms of shocks to sovereign bond yields and sovereign SCDS spreads, the contributions from the countries' own debt levels are relatively small except for the bond yields of Greece. For "core countries" of France, Germany, and UK, their own sovereign bond yields contribute as much to their own *r* and *scds* as these variables from other countries in the "core countries" group. Shocks of sovereign CDS spreads of France and Germany also share these similarities whereas the sovereign CDS spreads of UK are under greater influences from global financial factors *baa* and *vdax*. In the cases of "distressed countries", Ireland and Italy shared similar characteristics with other countries, except that influence from other "distressed countries" is also visible. Therefore we find a clear evidence that contagion from other country-variable as well as financial market factors help contribute to the increase of Greek sovereign bond yields.

As for the banking sectors, using France as a benchmark, a shock to its *seq* can be largely attributed to its own banking sector, its sovereign CDS spreads, the banking sector indices for other core/distressed countries. Comparing to France, the German *seq* is less under the influence of its own banking sector and its own CDS spreads, but more under the influence from other core countries. Greece and Ireland are under more influences from other distressed countries, whereas Italy's own banking sector contribute more to its own shock. In the case of UK, the global financial climate represented by credit risk premium, liquidity risk premium and market volatility contribute more to the shock to UK's banking sector, which is less influenced by the macroeconomic risk in other European Countries.

Table 4.7: **Generalised Forecast Error Variance Decomposition – Sovereign Long-term Bond Yields (**`r`**)**
This table reports the generalised forecast error variance decomposition for long-term bond yields by shocks from other variables at a given horizon. GFEVD values are normalised to 100. Shocks from other variables are categorised into variables of the country itself, variables of other countries in "core" country group or "distressed" country group. The specific country is excluded from the country group (core/distressed) that it belongs to.

Horizon	Panel [A]: Self					Panel [B]: Core					Panel [C]: Distressed					Panel [D]: Global		
	debt	r	scds	seq	y	debt	r	scds	seq	y	debt	r	scds	seq	y	baa	euribor-ois	vdax
FRANCE																		
1	0.32	25.63	0.25	0.74	0.14	0.58	40.10	0.97	1.51	1.42	1.10	9.65	1.12	2.92	0.75	0.40	0.87	0.80
2	0.32	25.38	0.31	1.27	0.23	0.68	39.47	0.94	1.50	1.24	1.07	9.28	1.18	3.06	0.70	0.49	1.02	1.24
4	0.38	24.93	0.36	2.01	0.50	0.85	38.24	0.95	1.48	1.09	1.08	8.95	1.26	3.23	0.66	0.56	1.17	1.75
8	0.53	24.32	0.38	2.63	1.30	1.12	36.87	0.98	1.52	1.16	1.19	8.86	1.27	3.43	0.70	0.44	1.08	1.73
12	0.69	23.77	0.39	2.85	2.09	1.38	35.84	1.02	1.59	1.35	1.36	8.86	1.25	3.50	0.77	0.35	0.93	1.51
GERMANY																		
1	0.12	20.95	0.29	0.72	0.20	1.24	36.77	1.70	3.76	1.08	0.66	1.92	1.87	1.27	0.58	3.36	3.94	5.25
2	0.26	19.40	0.42	1.00	0.19	1.30	34.17	2.17	4.25	1.20	0.76	1.85	1.77	1.36	0.61	4.53	4.82	6.19
4	0.60	17.98	0.50	1.06	0.26	1.35	32.12	2.48	4.48	1.45	0.92	1.87	1.64	1.37	0.69	5.58	5.42	7.05
8	1.07	17.81	0.42	0.83	0.71	1.34	32.60	2.24	4.11	2.02	1.12	2.09	1.54	1.27	0.97	5.28	4.67	6.59
12	1.17	18.36	0.42	0.71	1.23	1.30	34.22	1.95	3.62	2.41	1.17	2.36	1.54	1.19	1.22	4.27	3.67	5.29
GREECE																		
1	2.87	40.19	-	0.87	0.23	1.46	2.39	11.54	6.26	1.27	1.15	10.41	5.89	3.61	1.03	0.90	2.29	1.36
2	5.28	34.45	-	1.98	0.36	1.59	2.74	10.77	7.15	1.72	1.34	10.06	5.00	3.64	1.58	1.23	3.22	1.16
4	10.00	25.99	-	4.08	0.70	1.75	3.12	9.01	7.60	2.39	1.63	9.80	4.25	3.57	2.36	1.49	4.27	1.02
8	15.04	18.13	-	6.44	1.36	1.88	3.18	6.70	6.81	3.24	1.86	9.56	3.34	3.29	3.04	2.12	5.86	1.25
12	16.76	14.81	-	7.31	1.71	1.93	3.21	5.57	6.17	3.61	1.99	9.20	2.98	3.04	3.33	2.82	6.99	1.59
ITALY																		
1	0.11	23.14	4.37	2.35	0.14	1.01	19.70	5.29	4.79	1.82	3.63	17.73	3.44	3.09	1.46	1.00	0.52	1.53
2	0.15	23.38	4.28	2.30	0.16	1.07	19.78	4.88	4.64	1.91	3.63	17.88	3.44	3.08	1.48	0.90	0.81	1.37
4	0.21	23.52	4.14	2.20	0.21	1.21	19.81	4.23	4.36	2.12	3.68	17.82	3.35	3.07	1.54	0.93	1.54	1.15
8	0.33	23.22	3.81	1.98	0.32	1.44	19.50	3.49	4.19	2.44	3.73	17.21	3.13	3.09	1.61	1.09	2.76	1.35
12	0.42	22.78	3.61	1.80	0.45	1.50	19.33	3.12	4.20	2.66	3.72	16.76	2.91	3.08	1.62	1.30	3.65	1.57
UK																		
1	0.24	33.33	0.44	0.39	0.25	1.28	37.70	1.18	2.45	1.57	1.01	1.61	1.92	0.78	0.80	0.58	0.40	0.92
2	0.32	32.70	0.50	0.43	0.27	1.36	37.14	1.30	2.70	1.66	1.02	1.56	2.04	0.79	0.84	0.75	0.51	1.16
4	0.42	31.82	0.59	0.49	0.35	1.47	36.74	1.49	2.76	1.87	1.06	1.57	2.12	0.83	0.92	0.83	0.64	1.18
8	0.53	30.54	0.72	0.59	0.55	1.64	35.86	1.71	2.67	2.16	1.16	1.66	2.08	0.83	0.97	1.14	1.07	1.21
12	0.60	30.09	0.86	0.61	0.65	1.72	34.89	1.90	2.56	2.24	1.17	1.73	2.07	0.84	1.00	1.39	1.36	1.29

Table 4.8: **Generalised Forecast Error Variance Decomposition – Sovereign Credit Default Swaps (`scds`)**
Table 4.8 reports the generalised forecast error variance decomposition for sovereign credit default swaps by shocks from other variables at a given horizon. GFEVD values are normalised to 100. Shocks from other variables are categorised into variables of the country itself, variables of other countries in "core" country group or "distressed" country group. The specific country is excluded from the country group (core/distressed) that it belongs to.

Horizon	Panel [A]: Self					Panel [B]: Core					Panel [C]: Distressed					Panel [D]: Global		
	debt	r	scds	seq	y	debt	r	scds	seq	y	debt	r	scds	seq	y	baa	euribor-ois	vdax
FRANCE																		
1	0.24	0.21	23.97	10.11	0.27	1.04	1.46	22.91	5.60	1.53	0.84	2.21	8.56	1.81	0.46	2.44	1.17	7.21
2	0.25	0.22	23.82	10.46	0.31	1.03	1.38	22.09	5.58	1.54	0.81	2.10	8.30	1.84	0.44	2.55	1.17	8.17
4	0.31	0.23	23.74	10.78	0.39	1.00	1.35	21.63	5.63	1.59	0.85	2.05	8.24	1.90	0.45	2.42	1.01	8.65
8	0.45	0.25	23.78	10.74	0.59	1.04	1.37	21.95	5.84	1.80	0.96	2.15	8.57	1.97	0.52	1.73	0.74	7.70
12	0.55	0.28	23.67	10.48	0.78	1.11	1.43	22.47	6.05	1.91	1.05	2.29	8.87	2.03	0.58	1.31	0.62	6.50
20	0.71	0.31	23.45	9.90	1.03	1.24	1.50	23.17	6.32	2.10	1.22	2.41	9.08	2.10	0.66	1.02	0.52	4.93
GERMANY																		
1	0.28	0.81	19.33	6.69	1.85	1.17	1.25	28.12	10.61	1.08	1.26	0.80	3.85	1.58	0.57	2.05	1.30	6.69
2	0.37	1.08	18.42	7.18	1.75	1.21	1.24	27.24	10.95	1.05	1.20	0.76	4.01	1.74	0.55	2.49	1.58	6.53
4	0.54	1.36	18.02	7.62	1.63	1.26	1.27	26.41	10.96	1.05	1.16	0.73	4.27	1.89	0.58	2.92	1.80	5.99
8	0.89	1.68	18.50	8.25	1.53	1.31	1.34	25.85	10.42	1.12	1.13	0.75	4.73	1.99	0.63	2.61	1.63	4.74
12	1.16	1.84	19.10	8.58	1.52	1.39	1.35	25.53	9.94	1.21	1.15	0.81	5.03	2.02	0.68	2.20	1.46	3.77
20	1.39	1.98	19.96	9.02	1.61	1.44	1.37	25.36	9.38	1.31	1.15	0.87	5.36	2.02	0.72	1.64	1.28	2.73
ITALY																		
1	0.05	2.26	10.45	1.92	0.17	1.96	1.51	22.50	12.80	0.78	0.95	0.94	8.37	2.42	0.46	7.32	5.19	13.68
2	0.06	2.06	9.73	1.93	0.21	1.97	1.68	21.66	12.90	0.81	0.92	0.90	8.08	2.48	0.45	8.38	5.54	13.89
4	0.09	1.90	9.65	2.01	0.32	2.00	1.95	20.76	12.72	0.88	0.96	0.86	8.15	2.58	0.50	9.09	5.41	13.78
8	0.17	2.02	10.99	2.14	0.61	2.16	2.29	20.03	11.85	1.02	1.15	0.95	9.31	2.92	0.66	8.30	4.75	12.21
12	0.24	2.21	12.38	2.19	0.98	2.31	2.54	19.68	11.15	1.17	1.31	1.06	10.43	3.26	0.81	7.07	4.11	10.49
20	0.38	2.49	14.24	2.24	1.45	2.56	2.83	19.37	10.07	1.38	1.55	1.19	11.98	3.74	1.07	5.35	3.22	8.02
UK																		
1	0.45	0.30	19.66	1.92	0.59	1.43	1.31	20.33	9.35	1.59	0.74	0.89	5.45	1.61	0.70	7.62	5.05	13.02
2	0.89	0.30	14.80	1.36	0.94	1.66	1.45	16.80	8.89	1.94	0.85	0.87	4.28	1.73	0.81	11.26	6.08	16.96
4	2.25	0.34	9.57	1.00	1.68	2.03	1.74	12.37	7.66	2.72	1.10	0.92	3.14	1.96	1.13	15.02	6.04	20.75
8	5.16	0.59	6.56	1.47	3.21	2.66	2.30	9.94	6.47	4.65	1.66	1.07	2.61	2.20	1.94	13.92	5.01	18.62
12	7.19	0.75	5.56	1.97	4.28	3.28	2.68	9.96	6.60	6.20	2.06	1.15	2.44	2.14	2.41	10.72	5.43	14.06
20	8.97	0.85	4.42	2.33	5.50	3.91	2.79	10.77	7.29	7.82	2.29	1.09	2.17	1.83	2.73	7.50	5.98	9.84

Table 4.9: **Generalised Forecast Error Variance Decomposition – Sovereign Banking Sector Equity Returns (`seq`)**
Table 4.9 reports the generalised forecast error variance decomposition for sovereign banking sector equity returns by shocks from other variables at a given horizon. GFEVD values are normalised to 100. Shocks from other variables are categorised into variables of the country itself, variables of other countries in "core" country group or "distressed" country group. The specific country is excluded from the country group (core/distressed) that it belongs to.

Horizon	Panel [A]: Self					Panel [B]: Core					Panel [C]: Distressed					Panel [D]: Global		
	debt	r	scds	seq	y	debt	r	scds	seq	y	debt	r	scds	seq	y	baa	euribor-ois	vdax
FRANCE																		
1	0.21	0.28	12.74	28.04	1.04	1.14	1.08	7.83	10.83	1.99	0.39	1.47	3.05	9.31	0.39	1.81	1.71	9.73
2	0.24	0.30	13.08	27.19	1.16	1.13	1.10	7.96	10.56	2.11	0.40	1.53	3.04	8.78	0.40	1.91	1.64	10.43
4	0.30	0.31	13.32	26.73	1.41	1.12	1.12	8.02	10.54	2.28	0.43	1.55	3.02	8.52	0.44	1.78	1.45	10.58
8	0.48	0.33	13.27	26.55	1.92	1.16	1.19	8.08	10.88	2.64	0.54	1.61	3.03	8.63	0.56	1.25	1.07	9.61
12	0.66	0.35	13.08	26.26	2.39	1.27	1.24	8.15	11.35	2.96	0.67	1.66	3.06	8.71	0.66	0.94	0.84	8.35
GERMANY																		
1	0.12	0.26	5.41	18.90	1.92	1.25	1.04	15.47	18.15	1.39	0.89	0.44	2.17	3.22	0.50	3.13	4.67	13.54
2	0.14	0.32	5.51	18.56	1.57	1.30	1.11	15.34	17.47	1.34	0.93	0.44	2.20	3.22	0.50	4.15	5.52	12.62
4	0.19	0.40	5.52	18.57	1.20	1.34	1.26	14.98	16.62	1.38	1.02	0.47	2.28	3.28	0.57	5.24	5.81	11.86
8	0.37	0.49	5.55	19.85	0.99	1.45	1.39	14.50	15.98	1.66	1.12	0.53	2.66	3.55	0.82	5.26	5.22	10.27
12	0.62	0.54	5.60	21.28	0.94	1.54	1.46	14.15	15.54	1.91	1.17	0.59	3.04	3.86	1.05	4.57	4.67	8.86
GREECE																		
1	1.65	0.37	-	26.34	0.65	1.59	2.24	12.24	16.65	2.60	0.97	2.13	4.01	5.31	1.26	4.99	1.67	9.10
2	1.44	0.37	-	24.73	0.88	1.70	2.21	11.83	16.16	2.81	0.93	2.04	4.05	5.36	1.12	6.00	1.82	10.16
4	1.27	0.38	-	24.37	1.33	1.83	2.21	10.73	15.29	3.27	0.96	1.94	4.09	5.54	1.06	6.77	1.72	10.60
8	1.28	0.51	-	26.55	2.41	1.98	2.54	9.31	13.58	4.07	1.15	2.01	4.16	6.01	1.15	5.69	1.62	8.89
12	1.34	0.63	-	28.51	3.29	2.08	2.84	8.22	12.13	4.74	1.36	2.08	4.11	6.16	1.32	4.74	1.76	7.00
ITALY																		
1	0.12	1.19	1.22	12.49	0.19	1.64	0.99	14.87	26.19	4.00	0.33	2.12	3.42	7.80	0.46	3.48	2.55	10.39
2	0.18	1.19	1.18	12.18	0.20	1.68	1.04	14.61	25.57	4.13	0.34	2.09	3.39	7.69	0.47	4.22	2.85	10.24
4	0.30	1.18	1.17	12.39	0.24	1.83	1.11	13.82	24.83	4.38	0.38	2.02	3.36	7.73	0.53	4.99	2.93	9.76
8	0.52	1.23	1.22	13.62	0.40	2.15	1.16	12.62	24.00	5.14	0.45	2.17	3.48	8.26	0.67	4.71	2.61	8.30
12	0.68	1.31	1.24	14.66	0.62	2.44	1.22	11.72	23.47	6.02	0.50	2.33	3.51	8.78	0.83	4.07	2.26	6.88
UK																		
1	0.37	0.20	1.07	13.40	1.51	2.11	2.69	5.68	10.48	2.89	0.58	0.60	0.50	1.44	0.89	13.73	11.94	17.85
2	0.55	0.20	0.68	9.77	1.75	2.25	2.44	4.83	9.65	2.71	0.59	0.60	0.50	1.43	0.76	16.94	12.41	20.44
4	0.90	0.23	0.77	6.42	2.21	2.34	2.29	4.08	8.32	2.69	0.68	0.65	0.64	1.46	0.80	19.51	11.80	23.17
8	1.82	0.36	2.02	4.47	3.25	2.50	2.42	4.35	6.87	3.02	0.93	0.76	1.37	1.52	1.12	19.42	9.99	22.28
12	2.58	0.48	3.61	3.80	4.15	2.66	2.67	5.97	6.18	3.49	1.17	0.86	2.32	1.57	1.40	17.26	8.44	19.44

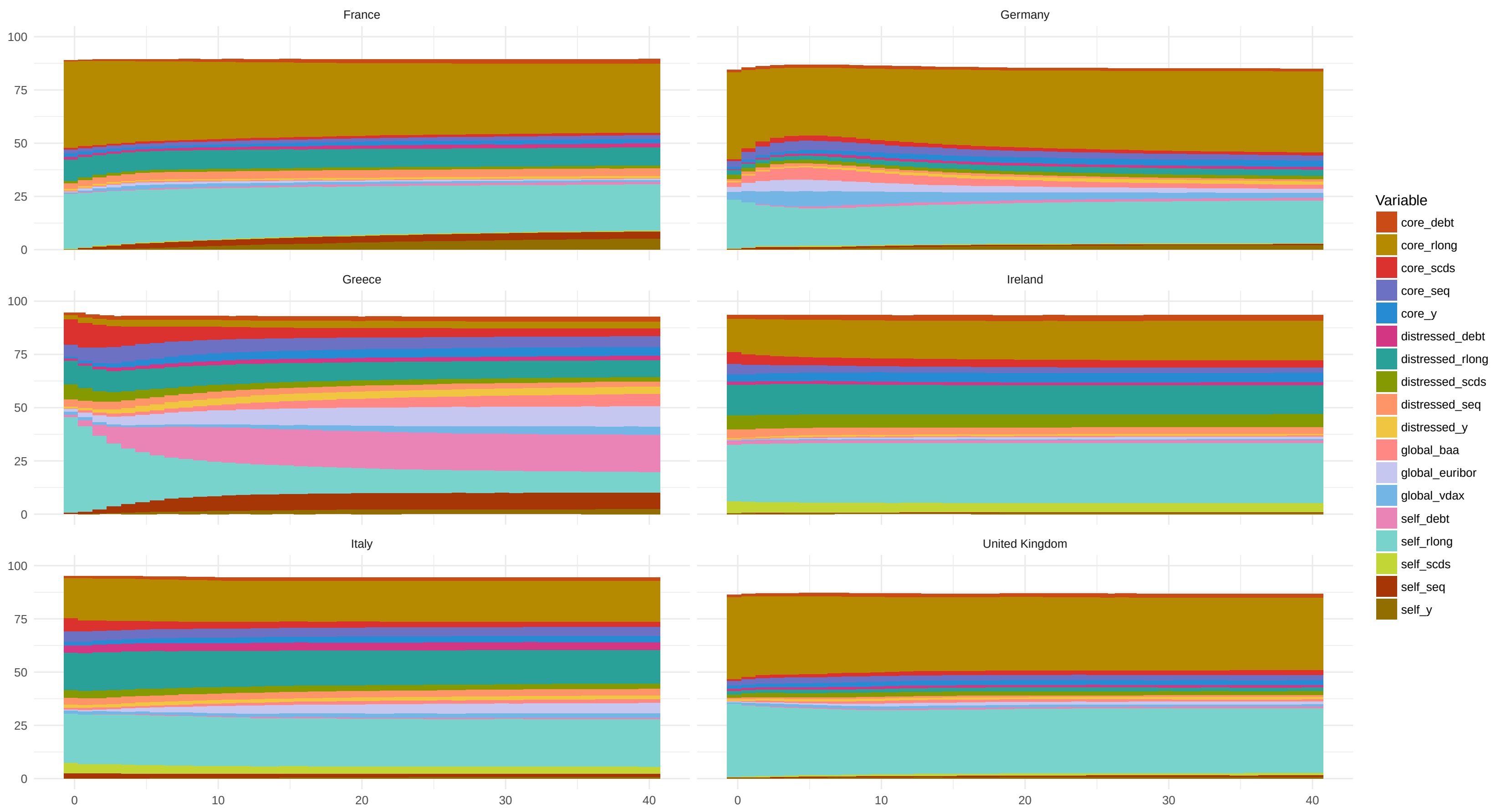

Figure 4.17: **GFEVDs: +1 se shock to sovereign bond yields**
The figure illustrates the relative contribution of each variables listed to the variable of interest in respective countries. Values are normalised to sum up to 100.

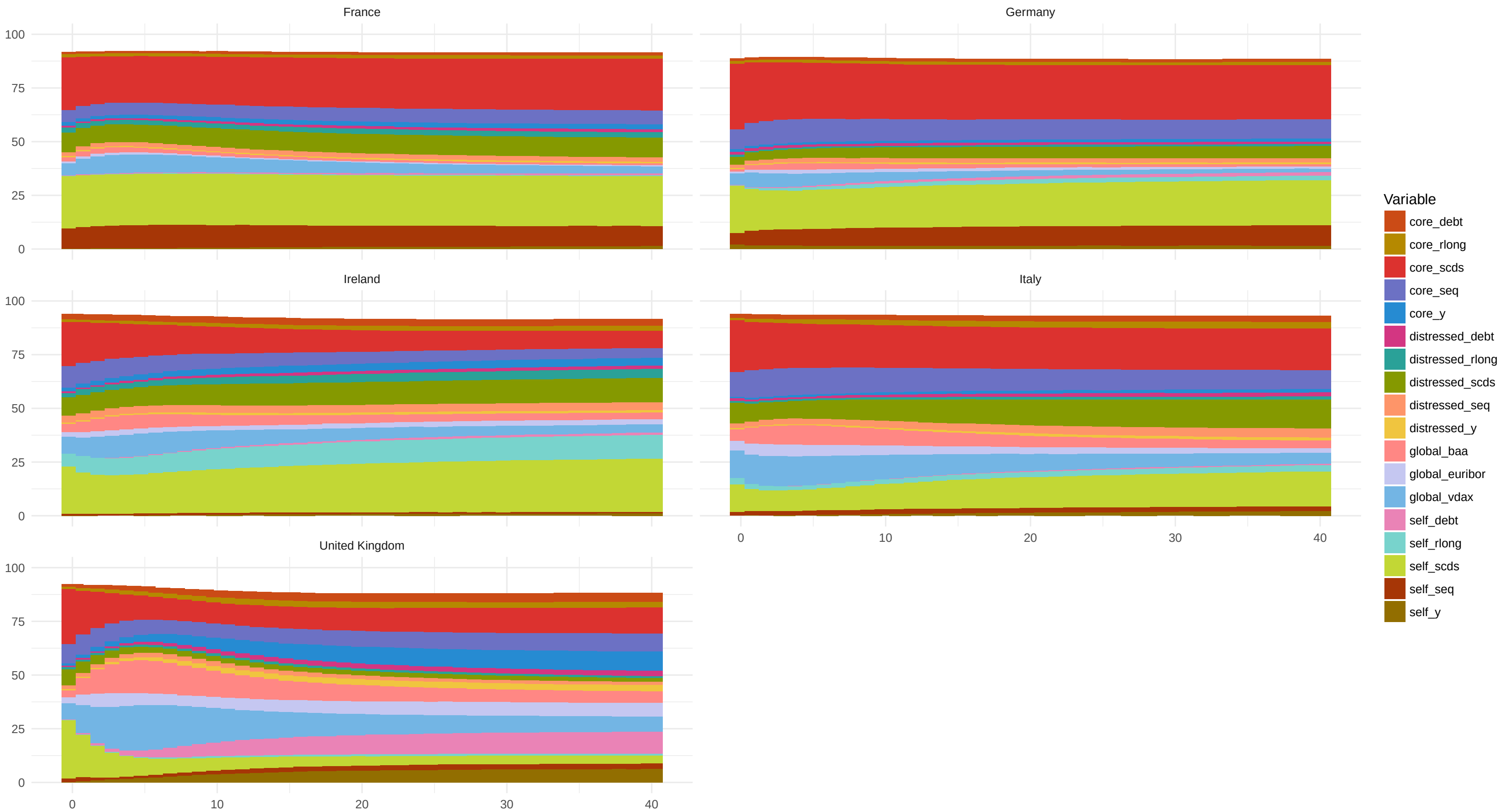

Figure 4.18: **GFEVDs: +1 se shock to sovereign CDS spreads**
The figure illustrates the relative contribution of each variables listed to the variable of interest in respective countries. Values are normalised to sum up to 100.

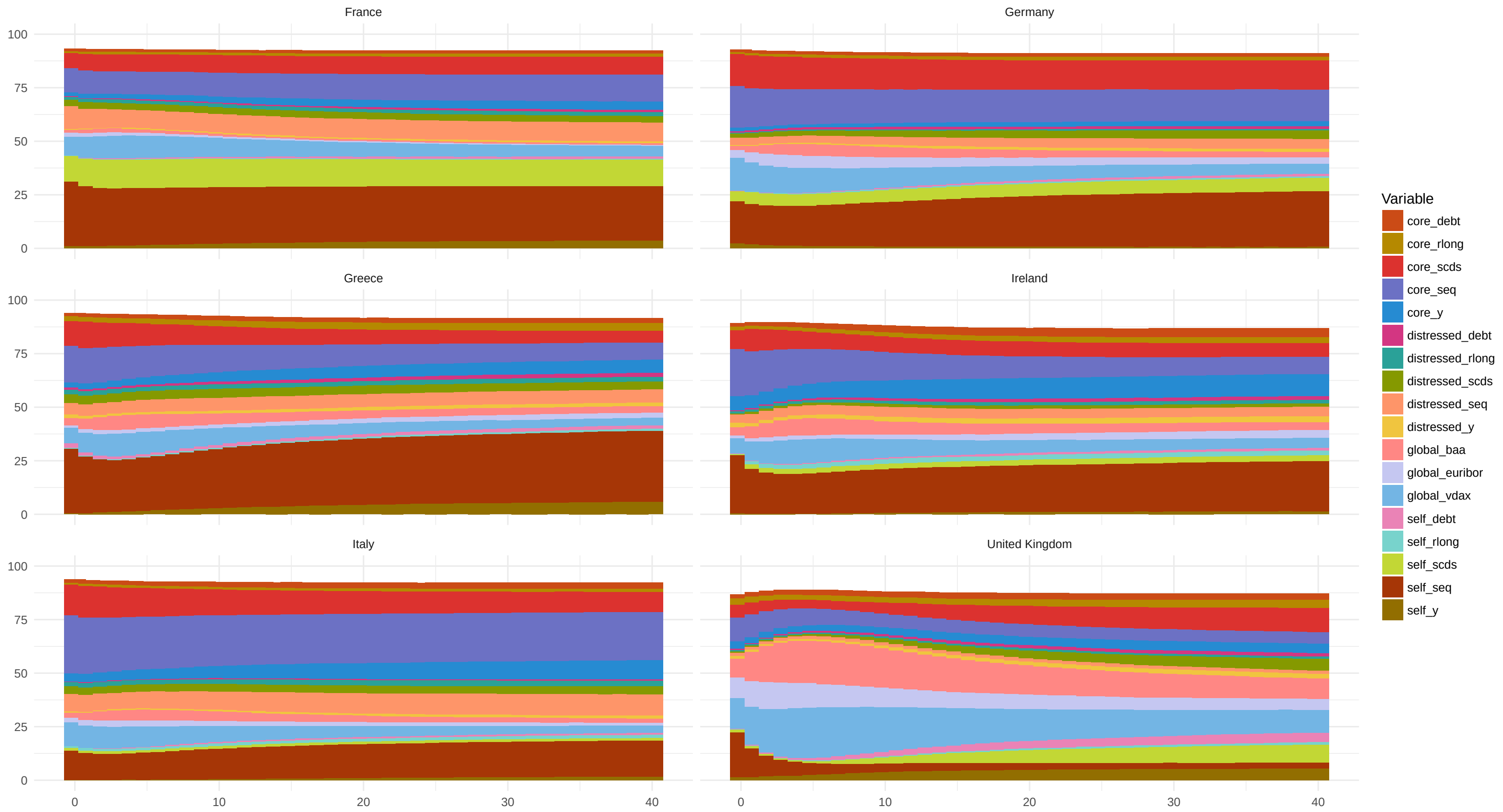

Figure 4.19: **GFEVDs: -1 se shock to banking sector equity returns**
The figure illustrates the relative contribution of each variables listed to the variable of interest in respective countries. Values are normalised to sum up to 100.

4.7 Conclusions

In this study we examine the implications of sovereign distress to the three markets: the sovereign bond markets, the sovereign CDS markets, and the national banking sector. The Global Vector-Autoregressive model (*GVAR*) allows us to model the dynamics among different domestic markets inside a supranational framework. We investigate the impact to the three markets of interest, of sovereign distress represented by macroeconomic shocks of fiscal burden and economic slowdowns as well as financial shocks of credit risk, liquidity risk and market volatility. We also examine the origins of shocks in these markets that can be attributed to the influences from the domestic/foreign markets and global factors.

To what extent are the sovereign risk spillover effects and how do the effects affect the financial markets? In Chapter 3 we discuss the effects of risk spillovers from sovereign countries, whereas in this chapter we further discuss the roles of risk originators and receptors. Among the "distressed countries" that are often regarded as originators of sovereign risk spillovers which impose systemic risk to the financial markets, we find the results are heterogenous by each country. Specifically, the scenarios of macroeconomic shocks originated from Germany, Portugal and Italy have strong spillover effects that contribute to the sovereign risk of other countries, as well as the financial markets in most countries. In the case of Greece, our results show that as an originator of risk its impact is modest and it is more under the influence of other distressed countries, which is in line with the general findings in Chapter 3.

Our results on the roles of countries in the risk spillovers scenarios are also generally in line with the findings in previous literature. In a similar *GVAR* framework, Gray (2013) simulates the adverse shocks to other countries from the *GIIPS*[9] country group and show that Greece is among the highest affected financial markets from

[9] Greece, Ireland, Italy, Portugal, and Spain.

outside influence, resulting in a 1.4% drop in its GDP and also in a 0.5% drop during the simulation horizon. In the study of price discovery mechanisms of Palladini and Portes (2011), the authors also show that the fundamental default risk as revealed in the bond spreads of the Greek government bonds is exacerbated by the influences from its CDS spreads, implying the receptor status of risk spillovers. The results in the static $\Delta CoVaR$ analysis in Fong and Wong (2012) also find that Greece and Portugal are the two most affected countries from risk spillovers, while their spillovers to other countries are relatively moderate. In general, our results are in line with the previous findings in the sovereign risk contagion literature and we believe our results are robust.

As for the implications to the financial sectors, our results regarding the banking sector returns show that the impact from weak economic growth is generally greater than impact from debt shocks, and there are strong effects to the financial sectors following the economic slowdowns of the EU economic powerhouses of Germany, France and UK. In addition, comparing to the banking sector returns of other countries which are influenced by EU cross-border sources, the returns of UK financial institutions are under greater influences of global financial factors.

From the perspective of policy-makers, providing support to countries of risk originations is crucial in terms of preventing the realisation of systemic events. In addition, how the sources of risk spillovers and the levels of relevant impact are identified influence the decisions regarding the timings and degrees of intervention policies. Our findings in terms of the dynamics of sovereign risk spillovers help contribute to the understanding of sovereign risk impact and provide information regarding the safeguarding of financial markets from sovereign risk impact.

Appendix 4.A Appendix

Table 4.10: **Variable Definitions and Constructions**
This table reports the definitions and constructions of variables used in this study. Constructed variables are denoted in lowercase letters and their raw forms are denoted in capital letters.

Variable	Definition	Explanation	Source
`y`	$y = \Delta ln(\frac{\text{NOMINAL GDP}}{\text{GDP DEFLATOR}})$	Real GDP growth. In the cases of non-Euro economies of Denmark, Sweden and UK, exchange rates wrt. Euro are taken into account.	OECD
`debt`	$debt = 100 \times \frac{GOVT.DEBT}{NOMINALGDP}$	Ratio of government debt to GDP	Eurostat
`r`	$r = ln(1 + \frac{\text{GOVT. BOND YIELD}}{100})$	Log of long term government bond yield, in gross interest rate form	Datastream
`scds`	$scds = ln(1 + \frac{\text{SOV. CDS}}{100})$	Log of 5 year sovereign credit default swap spreads, in gross interest rate form	Datastream
`seq`	$seq = ln(1 + \frac{\text{SOV. BANK EQUITY RETURN}}{HICP})$	Log of real banking sector equity returns*	Thomson One
`vdax`	$vdax = ln(VDAX\_NEW)$	Log of the implied volatility of the German stock index DAX	Datastream
`euribor-ois`	$euribor - ois = ln(1 + \frac{EURIBOR-EONIA}{100})$	Log of the spreads between 3 month EURIBOR rate and EONIA, in gross interest rate form	ECB
`baa`	$baa = ln(BAA - AAA)$	Log of the spreads between moody's BAA and AAA indices	Datastream

* The banking sector return for each country is calculated from the return of a banking sector index, which is constructed as the index of equity prices of commercial banks listed in their home country stock exchanges, weighted by their total assets.

Table 4.11: **Entities for Sovereign Banking Sector Equity**

Entity Name	Quote Symbol	Sedol	Country	Exchange
BKS Bank AG	BKS-VI	4082480	AUT	XWBO
Osterreichische Volksbanken AG	VBPS-VI	4664565	AUT	XWBO
Oberbank AG	OBS-VI	4081294	AUT	XWBO
Bank FUR Tirol Und Vorarlberg AG	BTS-VI	4082491	AUT	XWBO
Volksbank Vorarlberg	VVPS-VI	4932961	AUT	XWBO
Erste Group Bank AG	EBS-VI	5289837	AUT	XWBO
KBC Groep NV	KBC-BT	4497749	BEL	XBRU
Dexia	DEXB-BT	7147610	BEL	XBRU

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Table 4.11 – *Continued from previous page*

Entity Name	Quote Symbol	Sedol	Country	Exchange
DVB Bank SE	DVB-FF	4270489	DEU	XFRA
MLP AG	MLP-FF	5720273	DEU	XFRA
Merkur Bank Kgaa	MBK-FF	5641084	DEU	XFRA
Oldenburgische Landesbank AG	OLB-FF	4657855	DEU	XFRA
Deutsche Bank AG	DBK-FF	5750355	DEU	XFRA
Comdirect Bank AG	COM-FF	5975266	DEU	XFRA
Aareal Bank AG	ARL-FF	7380062	DEU	XFRA
IKB Deutsche Industriebank AG	IKB-FF	5169865	DEU	XFRA
Salling Bank A/S	SALB-KO	4771799	DNK	XCSE
Norresundby Bank A/S	NRSU-KO	4645399	DNK	XCSE
Ostjydsk Bank A/S	OJBA-KO	4660767	DNK	XCSE
Vestjysk Bank A/S	VJBA-KO	B00HQS0	DNK	XCSE
Kreditbanken A/S	KRE-KO	5712021	DNK	XCSE
Skjern Bank A/S	SKJE-KO	7454439	DNK	XCSE
Totalbanken A/S	TOTA-KO	B1W3ZK8	DNK	XCSE
Lan & Spar Bank A/S	LASP-KO	4529363	DNK	XCSE
Djurslands Bank A/S	DJUR-KO	B013KC9	DNK	XCSE
Mons Bank A/S	MNBA-KO	4601744	DNK	XCSE
Hvidbjerg Bank A/S	HVID-KO	4449610	DNK	XCSE
Nordfyns Bank A/S	NRDF-KO	4644998	DNK	XCSE
Lollands Bank A/S	LOLB-KO	B0773F9	DNK	XCSE
Sydbank A/S	SYDB-KO	B06JSP1	DNK	XCSE
Nordjyske Bank A/S	NORDJB-KO	B134MD2	DNK	XCSE
Gronlandsbanken A/S	GRLA-KO	4391090	DNK	XCSE
Spar Nord Bank A/S	SPNO-KO	B14LS01	DNK	XCSE
Ringkjobing Landbobank	RILBA-KO	B105JH1	DNK	XCSE
Fynske Bank AS	SVEND-KO	7207019	DNK	XCSE
Danske Bank A/S	DANSKE-KO	4588825	DNK	XCSE
Jyske Bank AS	JYSK-KO	B0386J1	DNK	XCSE
Banco Santander SA	SAN-MC	5705946	ESP	XMCE
Banco Popular Espanol SA	POP-MC	BBHXPN6	ESP	XMCE
Banco Bilbao Vizcaya Argentaria SA	BBVA-MC	5501906	ESP	XMCE
Banco De Sabadell SA	SAB-MC	B1X8QN2	ESP	XMCE
Bankinter SA	BKT-MC	5474008	ESP	XMCE
Alandsbanken ABP	ALBAV-HE	4019927	FIN	XHEL

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Table 4.11 – *Continued from previous page*

Entity Name	Quote Symbol	Sedol	Country	Exchange
Credit Industriel Et Commercial	CC-FR	5487471	FRA	XPAR
Banque Reunion	BQRE-FR	5286173	FRA	XPAR
Credit Agricole Ile De France	CAF-FR	7110463	FRA	XPAR
Societe Generale	GLE-FR	5966516	FRA	XPAR
Viel Et CIE	VIL-FR	5962417	FRA	XPAR
Natixis	KN-FR	B1HDJL2	FRA	XPAR
Credit Agricole Toulouse	CAT31-FR	4230171	FRA	XPAR
BNP Paribas	BNP-FR	7309681	FRA	XPAR
Crcam Ille-Village CCI	CIV-FR	4202448	FRA	XPAR
Crcam Normandie Seine	CCN-FR	7121153	FRA	XPAR
Credit Agricole Morbihan	CMO-FR	4230449	FRA	XPAR
Crcam Nord De France CCI	CNF-FR	B0VTSP6	FRA	XPAR
Crcam Atlantique Vendee	CRAV-FR	7397879	FRA	XPAR
Credit Agricole Alpes Provences	CRAP-FR	5585148	FRA	XPAR
Credit Agricole SUD Rhone Alpes	CRSU-FR	5082304	FRA	XPAR
Credit Agricole Loire-H-Loire	CRLO-FR	4253736	FRA	XPAR
Credit Agricole SA	ACA-FR	7262610	FRA	XPAR
Credit Agricole Touraine	CRTO-FR	4426624	FRA	XPAR
Credit Foncier De Monaco	MLCFM-FR	BFTW6M5	FRA	XPAR
Royal Bank Of Scotland Group PLC	RBS-LN	B7T7721	GBR	XLON
Arbuthnot Banking Group PLC	ARBB-LN	792233	GBR	XLON
Close Brothers Group PLC	CBG-LN	766807	GBR	XLON
Lloyds Banking Group PLC	LLOY-LN	870612	GBR	XLON
Barclays PLC	BARC-LN	3134865	GBR	XLON
HSBC Holdings PLC	HSBA-LN	540528	GBR	XLON
Standard Chartered PLC	STAN-LN	408284	GBR	XLON
Alpha Bank SA	ALPHA-AT	4235864	GRC	XATH
Attica Bank SA	TATT-AT	BBG9VR1	GRC	XATH
Eurobank Ergasias SA	EUROB-AT	BBL58B7	GRC	XATH
National Bank Of Greece SA	ETE-AT	BB36BJ7	GRC	XATH
Bank Of Piraeus SA	TPEIR-AT	BBFL4S0	GRC	XATH
Allied Irish Banks PLC	AIB-DB	4020684	IRL	XDUB
Bank Of Ireland	BIR-DB	3070732	IRL	XDUB

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Table 4.11 – *Continued from previous page*

Entity Name	Quote Symbol	Sedol	Country	Exchange
Mediobanca Banca DI Credito Fin SA	MB-MI	4574813	ITA	MTAA
Banca Popolare Emilia Romagna	BPE-MI	4116099	ITA	MTAA
Banca Intermobiliare	BIM-MI	4446398	ITA	MTAA
Banco DI Sardegna	BSRP-MI	4072533	ITA	MTAA
Unicredit	UCG-MI	B5M1SM3	ITA	MTAA
Banca Popolare DI Sondrio	BPSO-MI	4115223	ITA	MTAA
Unione DI Banche Italian	UBI-MI	7622225	ITA	MTAA
Banca Popolare DI Milano	PMI-MI	4072168	ITA	MTAA
Intesa Sanpaolo	ISP-MI	4076836	ITA	MTAA
Banca Carige	CRG-MI	7277528	ITA	MTAA
Banca Profilo	PRO-MI	5724587	ITA	MTAA
Credito Emiliano	CE-MI	7135251	ITA	MTAA
Banca Monte DEI Paschi	BMPS-MI	BM7SBM9	ITA	MTAA
Banco DI Desio E Brianza	BDB-MI	4115740	ITA	MTAA
Banca Popolare Etruria Lazio	PEL-MI	B8DPTG6	ITA	MTAA
Banco Popolare	BP-MI	BKJ9QS7	ITA	MTAA
ING Groep NV	INGA-AE	7154182	NLD	XAMS
Van Lanschot NV	LANS-AE	5716302	NLD	XAMS
Banco Comercial Portugues	BCP-LB	5812493	PRT	XLIS
Banco Espirito Santo SA	BES-LB	4058061	PRT	XLIS
Banco BPI SA	BPI-LB	5721759	PRT	XLIS
Swedbank AB	SWED'A-SK	4846523	SWE	XOME
Nordea Bank AB	NDA'SEK-SK	5380031	SWE	XOME
SEB 'A' SA	SEB'A-SK	4813345	SWE	XOME
Svenska Handelsbanken AB	SHB'A-SK	5703661	SWE	XOME

Chapter 5

Systemic Risk Spillovers in Tail-Dependence Network

5.1 Introduction

A network representation of the financial system depict individual market participants represented as nodes and various linkages from different channels are represented as edges. Similar to the network representation of other concepts of interconnectedness, from social networks to the contagion of epidemics, the outcomes of risk propagation are dependent on the structure of how financial network is formulated, and the fragility of the system is also dependent on the location where the initial shocks occurs (Allen and Babus, 2008). Early theory on the risk sharing aspect of network formulation suggests that an incomplete network structure where most entities are distant from each other is more prone to contagion and network resilience improves with more complete structures (Allen and Gale, 2000). However, empirical evidence document the contagion effects during the recent episodes of financial crises including the Global Financial Crisis of 2008-2009 and the Eurozone Sovereign

Crisis of 2010-2012 which suggests the existence of the high spillovers of systemic risk (Adrian and Brunnermeier, 2011; Acharya et al., 2012) and the rapid surges of network interconnectedness (Billio, Getmansky, Lo and Pelizzon, 2012). In the context of an increasingly globalised financial integration, further studies regarding interconnectedness of financial institutions from a global perspective is required to provide insights into how financial stability can be maintained.

Traditional approaches in macro-prudential regulation in systemic risk rely on market data of asset prices and equity values, as well as the balance sheet data of financial institutions. The $\Delta CoVaR$ measure by Adrian and Brunnermeier (2011, 2016), along the other measures such as the marginal expected shortfall of Acharya et al. (2010, 2012) has been widely adopted in academia for the study of systemic risk. Regulators also adopt these systemic risk measures in their tool sets to monitor the stability of the financial market. The European Central Bank provides its own estimates of $\Delta CoVaR$ for the banking sector and insurance sector as indicators for risk monitoring purposes. However, traditional systemic risk measures suffer from two drawbacks. Firstly, estimates of an individual institution's risk aggregate contributions and exposures to the "system" might not reflect the actual risk positions as it often ignores or averages the connectedness of the individual in the system, regardless of the heterogeneity of the individual's linkages. Financial institutions with similar aggregated exposures to the system might have different set of directly connected neighbours and thus different realised outcomes of impact given their respective routes of risk propagation. Secondly, as connectedness structures are ignored, these risk measures are not able to examine the microscopic dynamics of contagion occurring the system in multi-stage scenarios, which could underestimate the severity of negative externality during the times of market distress or financial crisis. Therefore a multidimensional approach to examine the risk contributions of individual institutions to the system, as well as the overall stability of the financial system is warranted.

The global financial system is not a centralised market but rather a complex network structure of multiple layers and clusters formed by the bilateral relationships of individual market participants. The interconnectedness of financial institutions can be attributed to different types of linkages which in turn could stem from counterparty risk of unsecured debt contracts (Furfine, 2003), indirect balance-sheet linkages and fire sales distress (Lagunoff and Schreft, 2001; De Vries, 2005), or the withdrawal of funding liquidity (Brunnermeier and Pedersen, 2009). Distress of one market participant not only imposes credit risk to its counterparties, but also lead to fire-sales of mark-to-market assets and the tightening of margins which result in further crowded trade and system-wide instability. On one hand, the risk sharing nature of financial network helps diversify idiosyncratic shocks, but on the other hand it facilitates the amplification of the externality of individual distress which contributes to the fragility of the system. In addition, the interconnectedness of financial institutions creates a moral hazard problem where they will be incentivised to increase their mutual linkages and benefit from them, and they will be deemed as "too-interconnected-to-fail" to financial regulators in order to prevent greater damages to financial stability. Therefore, finding ways to measure and monitor the financial interconnectedness remain an important task for regulators and policy-makers.

This study seeks to examine the impact of interconnectedness risk in a financial network that is formulated by the tail dependency of market returns. We define interconnectedness risk as the economic losses induced by the interconnectedness of financial institutions, when the impact initial shocks of market distress could be amplified by the propagation of stresses from one institution to another, resulting in greater market distress than the initial systemic risk spillovers. We extend the framework of systemic risk spillovers of Adrian and Brunnermeier (2016) to measure the pairwise systemic risk spillovers between two financial institutions and construct a global tail-dependence network formulated by the propagation of tail risk spillovers, using a globalised sample of financial institutions of commercial banks, broker-dealers, and insurance companies. We explore the network topology characteristics of the tail-dependence network, i.e. the level of interconnectedness of individual institutions represented by network centrality measures, as well as the distribution of connections. We then examine the impact of interconnectedness risk to the financial network system by assessing the network stresses induced by the propagation of systemic risk spillovers in the tail dependency network. Lastly, we examine the contributions of initial impact and interconnectedness measures to the realisation of network stresses.

We contribute to the strand of network analysis on financial systemic risk in several ways:

Firstly, we extend the aggregated systemic risk spillovers analytical framework to a pairwise level, where the individual-to-individual dynamics of risk spillovers are better captured. From the analytical framework of $\Delta CoVaR$ in Adrian and Brunnermeier (2016) on the aggregate risk spillovers relationship between individual entity and the system, we extend this approach to the pairwise risk spillovers relationship between financial institutions. The tail-dependence in market returns of financial institutions, estimated from the $\Delta CoVaR$ risk spillovers, is then used to construct the tail-dependence network.

Secondly, previous studies regarding entity interactions limit their scope at the top market participants, which also limit the validity of their research as small impact in the system can have greater consequences due to interlinkage. We greatly expand the scope of network interactions in market entities by allowing for the pairwise interactions of over 1,300 financial institutions in a dynamic rolling window fashion, which is larger than most empirical studies in this field (Billio, Getmansky, Lo and Pelizzon, 2012; Hautsch et al., 2012; Betz et al., 2015; Härdle et al., 2016). This large scope of analysis allows us to capture more subtle interactions among smaller market players that are typically identified by previous studies, and make the discussions on network interconnectedness and topological structure more applicable in real world scenarios.

Thirdly, we contribute to the understanding of the potential market collapse scenarios as discussed in the theoretical studies of Elliott et al. (2014) and Acemoglu et al. (2015), from the empirical perspective of the consequences of tail risk interconnectedness, by using the analytical framework of *DebtRank* in Battiston, Caldarelli, Puliga, Gabrielli et al. (2012); Bardoscia, Battiston, Caccioli and Caldarelli (2015) on the risk propagation of initial risk spillovers.

The following sections are organised as follows: In Section 5.2 we discuss the previous studies of financial network and our contributions. In Section 5.3 we discuss our methods in constructing tail-dependence network and assessing interconnectedness risk. In Section 5.4 we discuss our empirical strategy in data collection and variable construction. In Section 5.5 we discuss the characteristics of tail-dependence network and in Section 5.6 we discuss network stresses from interconnectedness risk. In Section 5.7 we provide the general conclusions of this study.

5.2 Related Literature

Our study can be related to the literature on systemic risk measures revealed by market series. Adrian and Brunnermeier (2011, 2016) propose a measure of the systemic risk spillovers of financial institutions from market series indicators, including market-valued asset returns and equity returns. The $\Delta CoVaR$ measure calculates the level of spillovers transferred to other market participants in the process when a financial institution experiences a distress event. Adrian and Brunnermeier (2016) examines the case of the systemic risk spillovers from an individual institution to the system as represented by a systemic portfolio series, but leaves open the research question of bilateral risk spillovers from one individual institution to another institution. We extend their study by investigating the pairwise risk spillover relationships of financial institutions.

Our study is also closely related to the study of a tail-dependence network. Hautsch et al. (2012) proposes a measure of the tail-dependence of financial institutions where the value-at-risk of one institution is co-dependent on the values-at-risk of other institutions. The tail-dependence is identified from a pool of potential candidate risk drivers of the series of other financial institutions, as well as common macro-financial variables, using a feature selection mechanism based on the $LASSO$ method (Tibshirani, 1996). This approach is also adopted by Bonaldi et al. (2015), Demirer et al. (2015), and Härdle et al. (2016) with feature selection variants including elastic net and adaptive $LASSO$ methods. Although variable shrinkage methods provide a way to identify tail-dependence among many financial institutions via feature selection, these studies are still limited by the feature size of their samples with about 100-200 financial institutions. Extending Adrian and Brunnermeier (2016)'s approach we construct the tail-dependence network by iteratively examine the risk spillover relationship between any two financial institutions in the sample, with the help of high performance computer clusters which enables us to build a larger sample pool of financial institutions.

Our study investigates the network topology structure regarding how the linkage patterns of individual nodes influence the overall behaviour of the network, where the theoretical and methodological foundations have been laid by previous studies by the various strands of financial network literature. Elliott et al. (2014) and Acemoglu et al. (2015) provide theoretical ground on how the interdependence of financial institutions and the diversification of shocks will determine the ultimate impact of an original shock to the system. Clauset, Shalizi and Newman (2009) proposes a tail power-law distribution which characterises the existence of highly interconnected nodes in real world network examples, and Cont et al. (2013) confirms that this network interconnectedness pattern is also observed in the interbank lending network. Billio, Getmansky, Lo and Pelizzon (2012) provides several centrality measures to capture the interconnectedness of financial institutions. Battiston, Puliga, Kaushik, Tasca and Caldarelli (2012) and Bardoscia et al. (2015) propose the DebtRank method to study the impact and stresses of network interconnectedness. Our study and results on network interconnectedness contribute to this literature on network characteristics.

We seek to provide empirical evidence of global financial cross-sector and cross-border linkages for regulators and policy-makers and provide justifications for their coordinated efforts in global financial stability. Billio, Getmansky, Lo and Pelizzon (2012) constructs a pairwise Granger Causality network of equity prices for United States financial sectors of commercial banks, broker-dealers, insurance companies and hedge funds. Betz et al. (2015) examines the risk spillovers of European banks and European sovereign states using CDS series. Demirer et al. (2015) studies the network volatility spillovers of large global banks. Our study is also related to these studies on financial institutions with cross-sector and cross-border market linkages.

5.3 Methodology

5.3.1 Constructing Tail-Dependence Network

Network $\Delta CoVaR$

The "$\Delta CoVaR$" concept of Adrian and Brunnermeier (2011, 2016) is a measure of directional tail dependence. "Systemic $\Delta CoVaR$" treats one financial institution as the originator of risk spillovers and the system (as represented by a systemic index or a systemic portfolio) as the receiver of risk, with the purpose of analysing the systemic risk contribution of the distress of one institution to the whole system. We extend the original framework to measure the pairwise directional tail dependence between two financial institutions, i.e. the "Network $\Delta CoVaR$" discussed in Adrian and Brunnermeier (2016, p. 1714).

Let X^i denotes the equity return of financial institution i and VaR_q^i denotes the $q^{th}-quantile$ Value-at-Risk of institution i. We refer to $CoVaR_q^{j|i}$ as the $q^{th}-quantile$ Value-at-Risk of institution j's equity return conditional on the event of institution i's equity return taking the value of VaR_q^i, and $\Delta CoVaR_q^{j|i}$ as the VaR difference conditional on i's VaR quantile shift[1]:

$$Pr(X^j|C(X^i = VaR_q^i) \leq CoVaR_q^{j|i}) = q \tag{5.1}$$

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|C(X^i=VaR_q^i)} - CoVaR_q^{j|C(X^i=VaR_{0.5}^i)} \tag{5.2}$$

We use quantile regression models for the series estimates of $VaR_{q,t}^i$, $CoVaR_{q,t}^{j|i}$ and $\Delta CoVaR_{q,t}^{j|i}$, which are modelled as the linear quantile estimates[2] based on lagged state

[1]We discuss the methodology of $\Delta CoVaR$ in Section 2.2.3.

[2]For the formulation of VaR and $CoVaR$ quantile regression models, please refer to the discussion in Adrian and Brunnermeier (2016, p. 1718). The choice of state variables in our study are discussed in Section 5.4.

variables $\mathbf{M}_{t-1}$.

$$\begin{aligned}
X_t^i &= \alpha_q^i + \gamma_q^i \mathbf{M}_{t-1} + \epsilon_{q,t}^i & (5.3)\\
X_t^{j|i} &= \alpha_q^{j|i} + \gamma_q^{j|i} \mathbf{M}_{t-1} + \beta_q^{j|i} X_t^i + \epsilon_{q,t}^{j|i} & (5.4)\\
VaR_{q,t}^i &= \hat{\alpha}_q^i + \hat{\gamma}_q^i \mathbf{M}_{t-1} & (5.5)\\
CoVaR_{q,t}^{j|i} &= \hat{\alpha}_q^{j|i} + \hat{\gamma}_q^{j|i} \mathbf{M}_{t-1} + \hat{\beta}_q^{j|i} X_t^i & (5.6)\\
\Delta CoVaR_{q,t}^{j|i} &= CoVaR_{q,t}^{j|i} - CoVaR_{0.5,t}^{j|i} & (5.7)\\
&= \hat{\beta}_q^{j|i} (VaR_{q,t}^i - VaR_{0.5,t}^i) & (5.8)
\end{aligned}$$

Note that from the empirical relationship between i and j in (5.6) and (5.8), when $\hat{\beta}_q^{j|i} = 0$, $CoVaR_{q,t}^{j|i}$ falls back to $VaR_{q,t}^j$ since there is no significant influence to j from the distress event of i, and naturally $\Delta CoVaR_{q,t}^{j|i} = 0$ when there is no risk spillovers from i to j. Therefore we denote $(i \to j) = 1$ as the existence of risk spillovers from i to j when we could not reject $Pr(> |t(\hat{\beta}_q^{j|i})|) \leq \alpha$, which confirms the presence of a significant $\beta_q^{j|i}$. For the inference of t-statistics we use the Huber Sandwich method for the heteroskedasticity-consistent estimates of standard errors[3] with a significance level of $\alpha = 1\%$.

Tail-Dependence Network and Centrality Measures

In order to construct the tail-dependence network we need to map out the contributions of the pairwise risk spillovers within the whole systemic spillovers that institution i imposes on the system. We first calculate $\Delta CoVaR_q^{sys|i}$, the systemic risk spillovers of institution i against the value-weighted systemic portfolio of the institutions in the sample, as well as the $i - j$ pairwise spillovers of institutions

[3]See the discussion in Koenker (2005, Section 3.2.3, p.74) for the quantile regression sandwich formula.

$\Delta \widetilde{CoVaR}_q^{j|i}$. Following Adrian and Brunnermeier (2016)'s discussions regarding systemic risk portfolio, we calculate $\Delta CoVaR_q^{j|i}$ as the $\Delta \widetilde{CoVaR}_q^{j|i}$ rescaled by value from $\Delta CoVaR_q^{sys|i}$ in a portfolio sense:

$$\Delta CoVaR_q^{j|i} = \frac{v_j}{\sum_{l,l \neq i}^{N} v_l} \Delta CoVaR_q^{sys|i}, \; v_l = \Delta \widetilde{CoVaR}_q^{j|i} \tag{5.9}$$

Given the risk spillover relationship calculated by $\Delta CoVaR_q^{j|i}$ between institutions i and j, we can then map out the tail dependency network of the financial system from the initial pairwise direct risk spillovers. We construct a $N \times N$ adjacency matrix $\mathbf{A}(a_{i,j} \in \{0,1\})$ where $a_{i,j} = 1$ if $(i \rightarrow j) = 1$ to denote the adjacency of two nodes, and a $N \times N$ spillover impact matrix $\mathbf{W}(w_{i,j} \in [0,1])$ where $w_{i,j} = -\Delta CoVaR_q^{j|i}$. We then construct the following two node centrality measures to describe the network topology structure: degree centrality and closeness centrality.

Degree centrality refers to the number of links between node i and its directly-connected neighbours[4]:

$$degree_i = \sum_{j=1}^{N} \sum_{i \neq j} (i \rightarrow j) \tag{5.10}$$

Degree centrality measures the direct connectedness of nodes. A node i with high degree not only means that more nodes are affected by i's distress or i is exposed to the distress events of more nodes, but also that node i is now more interconnected by serving as a hub node linking the spillovers of more nodes. Therefore, a financial network system with high degree centrality is more susceptible to the outbreak of systemic risk within a small group of individual institutions.

[4]For simplicity we refer to total-degree centrality for "degree" centrality in this context. Degree measures can be divided into two sub-measures: out-degree refers to the number of links with node i as the originator, and in-degree refers to the number of links with node i as the receiver. Total-degree that is the sum of out-degree and in-degree.

Closeness centrality refers to average steps it takes for the influence from node i to reach any other nodes in the network. The distress of i affects its directly linked neighbours, which then travels through the subsequent direct linkages of i's neighbours to other nodes, as long as there are direct routes to these nodes. Following Billio, Getmansky, Gray, Lo, Merton and Pelizzon (2012) we define $(i \xrightarrow{C} j)$ as a route from i to j with C steps, if there exists a unique C-step links from node i to node j via nodes k_1, k_2 to k_{C-1}:

$$(i \xrightarrow{C} j) = (i \rightarrow k_1) \times (k_1 \rightarrow k_2) \cdots \times (k_{C-1} \rightarrow j) \tag{5.11}$$

Define C_{ij} as the minimum[5] of all possible $(i \xrightarrow{C} j)$ links, which is the shortest possible path for the influence of i to reach j:

$$C_{ij} = \min_{C}\{C \in [1, N-1] : (i \xrightarrow{C} j)\} \tag{5.12}$$

As the measure for the overall connectedness or centrality of node i, $closeness_i$ denotes the average length of links from node i to all other nodes in the network:

$$closeness_i = \frac{1}{N-1} \sum_{i \neq j} C_{ij}(i \xrightarrow{C} j) \tag{5.13}$$

5.3.2 Measuring Interconnectedness Risk

Our study tries to examine the resilience of the global financial network regarding network-specific risks when facing severe distress. To do so, we need to evaluate the stresses induced by the network system due to the propagation of risk spillovers from the initial failures of individual institutions. Here we employ the "DebtRank"

[5] We use Dijkstra's Shortest Path algorithm for the calculation for C_{ij}, which iteratively eliminates inferior alternative routes until the shortest path is picked (Dijkstra, 1959).

method[6] of Battiston, Puliga, Kaushik, Tasca and Caldarelli (2012) and Bardoscia et al. (2015) as a measure to examine the impact of interconnectedness risk. DebtRank calculates the stresses (loss of economic values) to the financial network induced by the network structures due to the propagation of first failures, and the contributions of such stresses by financial institutions. In the context of our study, we use the term "network stresses" to specifically represent the losses of economic value induced by interconnectedness and risk propagation, and use the term "network impact" in a generalised sense to denote the interconnectedness impact, measured either as economic losses or as defaults.

Each node $j, j \in \{1, \ldots, N\}$ in the network is associated with two state variables: $h_j \in [0, 1]$ and $s_j \in \{U, D, I\}$. h_j records the current stress level of node j (represented as percentage equity losses), with $h_j = 0$ meaning no loss and $h_j = 1$ meaning a complete loss of economic value. s_j records the current state of the node, where $s_j = U$ meaning "undistressed", $s_j = D$ meaning "distressed" and $s_j = I$ meaning "inactive". In order to examine the network stresses caused by the distress of node i, we define the event $X_t^i = VaR_{q,t}^i = -\psi, \psi \in [0, 1]$ as the triggering event of systemic risk spillovers, meaning the distress event makes institution i suffer the realised VaR losses and its risk spillovers to other institutions are thus $\Delta CoVaR_q^{j|i}$. The impact matrix $\mathbf{W}$, as discussed in Section 5.3.1, then serves the routes of risk spillovers following i's distress. Therefore, the initial conditions for all nodes are as follows: $h_i(1) = \psi$; $h_j(1) = 0 \; \forall j \neq i$; $s_i(1) = D$; $s_j(1) = U \; \forall j \neq i$.

[6]DebtRank is originally proposed by Battiston, Puliga, Kaushik, Tasca and Caldarelli (2012) for the study of network impact of the US interbank debt holding market (hence its name), which borrows the concept from Google's PageRank algorithm (Page, Brin, Motwani and Winograd, 1999).

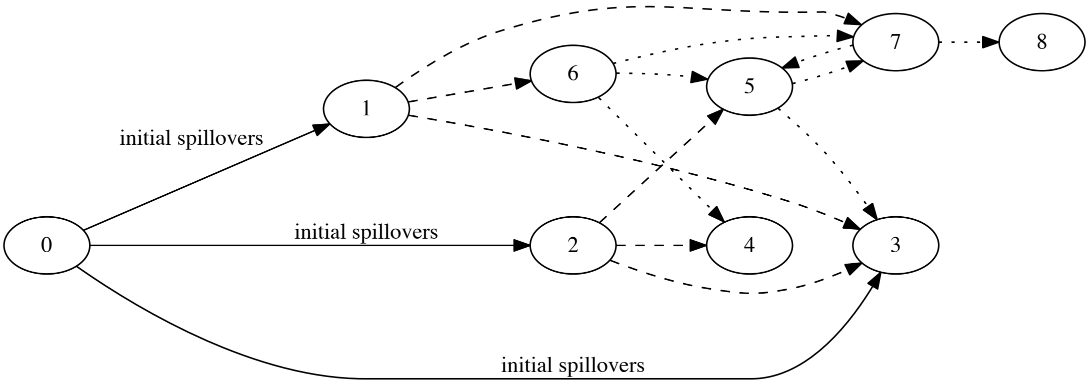


Figure 5.1: **Propagation of Risk Spillovers**
The impact of systemic risk spillovers from a node to other nodes in a financial network. The distress of node 0 is propgated to its directly connected neighbours 1, 2, 3, then the stresses of these nodes are then propagated to other nodes in the network in subsequent rounds.

The state variables of the nodes are then updated as follows:

$$h_i(t+1) = min\left\{1, h_i(t) + \sum_{j=1}^{N} \Lambda_{i,j}(t)h_j(t)\right\}, \tag{5.14}$$

$$\Lambda_{i,j}(t) = \begin{cases} W_{i,j}, & s_j(t) = D \\ 0, & s_j(t) \neq D \end{cases} \tag{5.15}$$

$$s_i(t+1) = \begin{cases} D, & h_i(t+1) > 0; s_i(t) \neq I \\ I, & s_i(t) = D \\ s_i(t), & otherwise \end{cases} \tag{5.16}$$

In other words, the stress level of an institution at the current period is cumulated by the sum of the intra-temporal cumulated shocks from its distressed neighbours. The risk propagation stops when all institutions in the system are either as unaffected or as inactive (in bankruptcy or finished passing over shocks). Note that banks that passed over shocks in previous periods (being in distress in that period) will stay as inactive for the remainder rounds, meaning that there is a unique route of shock propagation from a distressed note to its successor. This condition removes the possibility of multiple reverberations of shocks back to a distress node, which would potentially causing the shock to grow bigger and bigger. Nevertheless it is expected that a minor initial shock with relative small economic losses will cause a greater impact to the financial system, if the distressed origin node is linked to other nodes that are also interlinked deeper into the system.

r_i measures the network stresses by node i, which is the sum of the final cumulated stresses to all other nodes, weighted by their respective economic values in the system. And finally R denotes average network stresses imposed by a random node.

$$r_i = \sum_{j=1, j \neq i}^{N} h_j(T) v_j \tag{5.17}$$

$$R = \sum_{i=1}^{N} r_i v_i \tag{5.18}$$

We condition the shocks being propagated via the routes revealed by pairwise risk spillovers, which is a counterfactual analysis suitable for regulators to assess the initial or immediate impact of individual institutions' failures or the resilience of the system.

5.4 Data and Variable Specifications

5.4.1 Data and Variables for Financial Institutions

The equity market value returns for financial institutions are the focus of our study. As the focus of this study is on the financial network spillovers in the global financial system, we collect world-wide stock market data (in weekly frequency) and accounting data (in quarterly frequency) of publicly listed financial institutions that is available from Datastream and Thomson One, from January 2002 to June 2015. The financial institutions in our sample originate not only from major financial centres: United States, United Kingdom, the Eurozone (Germany, France, Italy, Spain, the Netherlands, etc.), Switzerland, Japan, and China, but also from other economies where large financial institutions could potentially be a triggering source of systemic risk. The availability of data on world-wide publicly-listed financial institutions allows us to capture the interconnectedness of individual financial institutions in a globalised system, as well as the interconnectedness clusters that are naturally formed by market relationships in financial zones. As for the types of financial institutions, we examine three financial sectors: commercial banks, broker dealers, and insurers, which is classified by the institutions' primary Standard Industrial Classification (SIC) codes[7].

The data filtering criteria is as follows:

1. they should be at least operational from 2006, and should at least have on average 1.5 quarterly observations per year for accounting data, and 30 weekly observations per year for stock market data, till the end of the sample period;

2. they should have at least 500 million USD of assets as of 2007;

3. they should be classified either as commercial banks (primary SIC 6000-6199), broker-dealers (primary SIC 6200-6299), or insurers (primary SIC 6300-6499);

4. the affiliated stock exchanges of their stock series should match the home countries in which they are registered, which means for multinational financial institutions we their home country firms.

As for data cleaning procedures, we use spline interpolation from the first non-

[7] For the classification of financial sectors we follow the definitions used in Billio, Getmansky, Lo and Pelizzon (2012).

missing observations to the last non-missing observations for accounting data, and then use spline interpolation to construct a size weighting matrix that is compatible with the weekly stock market data. Our sample consists of 1338 financial institutions with 705 weekly observations for each series from January 2002 to June 2015, which covers four periods of crisis: the early 2000s stock market crash (the dot-com bubble crash), 2007 Subprime Mortgage Crisis, 2008-2009 Global Financial Crisis, and 2010-2012 Eurozone Sovereign Crisis, all of which affect the globalised financial network to different extents. Summary statistics for the market value returns, broken down by market segments and economies, are reported in Table 5.1.

Table 5.1: **Summary Statistics - Market Value Returns (Weekly)**
Table 5.1 reports the summary statistics for market value returns for the top 10 countries with largest financial markets by size, and the rest of the world. The financial sectors are broken into three categories by primary SIC classifications.

Country	Obs.	Mean (%)	Median (%)	Std. (%)	Min (%)	Max (%)
			Commercial Banks			
Canada	8,460	0.22	0.06	3.31	-14.66	14.13
China	7,050	0.36	0.00	5.02	-18.98	22.55
France	11,280	0.16	0.08	4.16	-16.96	24.36
Germany	8,460	0.13	0.00	4.67	-18.96	29.11
Italy	13,395	0.15	0.05	5.15	-17.54	28.65
Japan	68,385	0.14	0.00	4.50	-25.87	44.33
Spain	3,525	0.21	0.19	4.99	-15.18	19.37
Switzerland	14,100	0.17	0.09	3.30	-17.88	22.69
United Kingdom	10,575	0.23	0.00	4.60	-19.19	24.58
United States	240,405	0.20	0.00	5.10	-48.16	56.25
Rest	285,525	0.34	0.00	5.52	-42.31	79.54
			Broker-Dealers			
Canada	2,820	0.24	0.00	4.87	-17.67	18.03
France	4,230	0.29	0.11	4.25	-13.35	19.37
Germany	4,230	0.00	0.00	6.15	-27.49	34.78
Italy	2,820	0.17	0.00	4.28	-13.70	20.70
Japan	21,150	0.29	0.00	6.91	-25.97	43.63
Spain	705	0.07	0.00	3.78	-11.14	11.73
Switzerland	6,345	0.18	0.00	4.30	-16.20	17.07
United Kingdom	16,215	0.25	0.00	4.98	-18.39	30.92
United States	21,150	0.36	0.00	5.36	-28.45	42.01
Rest	64,860	0.34	0.00	6.71	-43.49	81.37
			Insurers			
Canada	4,935	0.20	0.22	4.41	-29.33	27.22
China	1,410	0.53	0.00	5.68	-17.15	20.56
France	2,820	0.23	0.32	5.04	-18.10	18.65
Germany	2,820	0.07	0.00	4.70	-22.51	26.16
Italy	705	0.05	0.20	4.20	-12.63	12.18
Japan	2,820	0.26	0.00	5.94	-21.74	35.12
Spain	705	0.37	0.30	4.65	-11.75	15.33
Switzerland	2,820	0.22	0.23	5.00	-21.50	21.86
United Kingdom	7,755	0.24	0.12	4.43	-16.58	19.25
United States	49,350	0.30	0.04	5.47	-49.89	100.00
Rest	51,465	0.31	0.00	5.53	-38.35	58.00

5.4.2 State Variables for Quantile Regression Models

For state variables used in quantile regression models in Eq (5.5) and Eq (5.6) we follow the definition of Adrian and Brunnermeier (2016) for a small set of variable categories which capture the time variations in the mean and the volatility of market value returns and used in other quantile-based *CoVaR* studies (Fong and Wong, 2012; Lopez-Espinosa et al., 2012; Sharifova, 2012). State variables are common conditioning variables which influence both originators and receivers of the risk spillover relationships, and given the predominance of the United State financial market in the globalised financial industry we select the set of marco-financial indicators from the US market. The variable definitions are listed as follows:

1. `mkt_return`: equity market return proxied by the returns of S&P 500 index;
2. `vix`: equity market volatility proxied by the Volatility Index (VIX) of the Chicago Board Options Exchange (CBOE);
3. `credit_spread`: credit risk spread proxied by the spread of Moody's *Baa*-rated bonds and the ten-year US Treasury Bond rate;
4. `liquidity_spread`: liquidity risk spread proxied by the spread between three-month US repo rate and three-month US Treasury Bill rate;
5. `term_spread`: term structure spread (change in the slope of the yield curve) as the difference between ten-year US Treasury Bond rate and three-month US Treasury Bill rate;
6. `bond3m_d`: changes in the three-month US Treasury bill rate;
7. `financial_stress_d`: changes in the Financial Stress Index by the Federal Reserve Bank of St. Louis.

Table 5.2: **Summary Statistics - State Variables (Weekly)**

Variable	Obs.	Mean	Median	Std.	Min	Max
`mkt_return`	705	0.0011	0.0032	0.0241	-0.1459	0.1317
`vix`	705	20.0300	17.4200	9.3566	10.0200	79.1300
`credit_spread`	705	-0.7958	-0.6300	1.5773	-3.5100	3.6800
`liquidity_spread`	705	0.1178	0.0500	0.2112	-0.2400	1.1800
`term_spread_d`	705	-0.0016	0.0000	0.1139	-0.9500	0.6700
`bond3m_d`	705	-0.0023	0.0000	0.0796	-0.8600	0.4400
`financial_stress_d`	705	-0.0027	-0.0090	0.1364	-0.8570	1.3550

5.5 Tail-Dependence Networks

In this section we discuss result findings related to the characteristics of the tail dependency network.

5.5.1 Network $\Delta CoVaR$

Value-at-Risk Specification Tests

We construct $\Delta CoVaR$ using quantile regression models, and to evaluate the overall adequacy of our choice of state variables, here we implement three specification tests to examine the variable specification: unconditional coverage test of Kupiec (1995), conditional coverage test of Christoffersen et al. (2001), and duration test of Christoffersen and Pelletier (2004).

If the estimated series of Value-at-Risk is correctly specified, we would expect that the proportion of observed "hits" (VaR violations) should not be different from the specified VaR tail. The unconditional coverage test of Kupiec (1995) (proportion of failures test) examines whether the number of hits is consistent with the confidence level. The null hypothesis states that the proposed hit rate should not be significantly different from the observed hit rate:

$$H_0 : p = \hat{p} = \frac{x}{T}$$

The conditional coverage test of Christoffersen et al. (2001) improves the unconditional coverage test by taking into account the independence of hits. Assuming that the violation is modelled with a first order Markov chain procedure, and define the following:

$$\pi_0 = \frac{n_{01}}{n_{00} + n_{01}},\ \pi_1 = \frac{n_{11}}{n_{10} + n_{11}},\ and \pi = \frac{n_{01} + n_{11}}{n_{00} + n_{01} + n_{10} + n_{11}},$$

where $n_i j$ is the number of days when event j (1 if a hit occurs, otherwise 0) occurred under the condition that event i occurred on the previous day. The null hypothesis of the independence of violations states that π_0 and pi_1 should not be statistically different, and therefore the proportion of hit events preceded by non-hit events is equal to the proportion of hit events preceded by hit events.

The duration test of Christoffersen and Pelletier (2004) provides an augmented approach to examining the independence of Value-at-Risk violations, that the time lapses between hits should be independent of the time lapses since the last hit. Given the coverage rate/quantile q, the expected conditional duration of no hits should be $\frac{1}{q}$ periods and has no presence of memory effect. The authors show that the general duration process can be modelled as a Weibull process, and a memory-free duration process (as an exponential process) is a special case of the Weibull distributions with the memory parameter equalling 1.

We implement the three tests discussed above to our Value-at-Risk specifications. All three tests provide null hypotheses of specifications being adequate, therefore we report the proportions of individual p-values that are above significance levels.

As shown from Table 5.3, we confirm that our VaR specification based on quantile regression models is adequate.

Table 5.3: **Summary of Value-at-Risk Specification Tests**

Test	Unconditioanl Coverage Test	Conditional Coverage Test	Duration Test
ratio($p - value \geq 0.01$)	1.00	0.88	0.91
ratio($p - value \geq 0.05$)	1.00	0.85	0.83
ratio($p - value \geq 0.10$)	1.00	0.81	0.76
mean($p - value$)	0.88	0.66	0.40
No. of tests	1338		

Rolling Window Implementation

We account for the time variations in the network interconnectedness structure by using a rolling window implementation similar to Betz et al. (2015) over our sample period. For our sample period of $T = 705$ weeks, we construct a sub sample window of $W = 78$ weeks (on average 1.5 years) with the first $H = 8$ weeks as step length, which gives us $Q = \lceil \frac{T-W+1}{H} \rceil = 79$ windows spanning from January 2002 to January 2007. In each window, we examine the pairwise spillover relationships of $N = 1,338$ institutions in quantile-based $\Delta CoVaR$ models forming $N^2 - N = 1,708,906$ potential pairs. Therefore our rolling window implementation allows us to obtain results of network spillovers and interconnectedness structure as $N \times N \times Q$ cubes of pairwise adjacency and impact positions.

5.5.2 Network Topology Structures

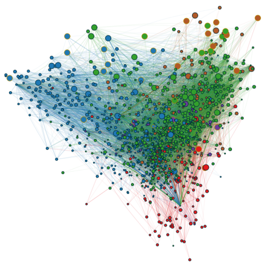
General Overview

The tail dependency network (as a weighted network plot) is constructed by the $\Delta CoVaR$ risk spillovers between two neighbouring financial institutions. A heavily interconnected institution is represented in the network as a node widely to other nodes, which will be placed in the center of the network graph when compared to other nodes whose linkages are more sparse. Nodes that have close direct/indirect connections with each other will also be clustered together to represent the relative "hubs" emerged in the network. In this way, a network that is densely connected and contains large number of nodes widely linked to other "central" as well as "periphery" nodes represents a heavily interconnected financial market, which is potentially synchronised and vulnerable to external shocks. On the contrary, a more sparsely linked financial network will be more resistant to a large external shock originated from a single source.

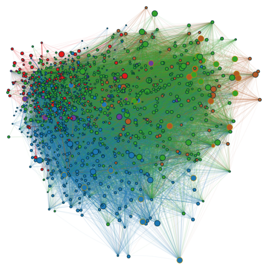
Figure 5.2 shows the general overview of the network structure in different periods, from the early stages of the 2007 Subprime Mortgage Crisis to the aftermath of the 2009 - 2010 Eurozone Crisis[8]. Since risk spillovers from the originator institution to the receiver institution are jointly determined by the risk positions of market returns of both institutions, when they face downturn pressures during times of financial stress, we observe widespread strong risk spillovers within the tail dependency network during crisis periods. When market recovers from systemic downturn pressures, risk positions of participants become less synchronised with common market shocks. The plots show that during crisis periods greater numbers of institutions are affected by the systematic intensification of individual pairwise risk spillovers resulting in potential systemic collapse of the financial network should external shocks realise. The subplots also show the clustering of nodes, that in moderate times financial institutions tend to be clustered by their economy zones, with the US and Japan being the most visible clusters. In contrast, cross-border financial downturns during crisis periods would remove the visible network clusters, and most of the individual market participants

[8]We define the start and end of crisis periods by certain major events relating to the crises, since market fluctuations tend to be around the occurrence of these events. For a brief list of events to be examined in this study, please refer to Table A.1.

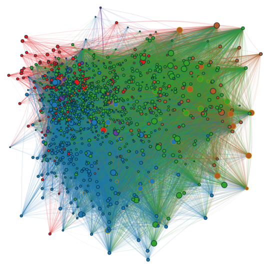
are collectively under the dominating influence of crises.



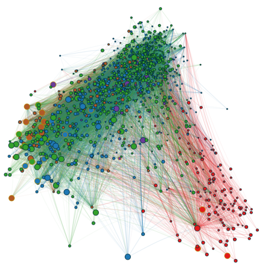
(a) August, 2007



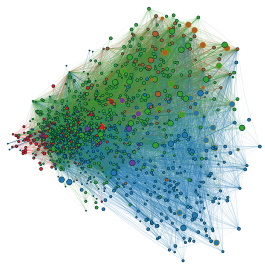
(b) September, 2008



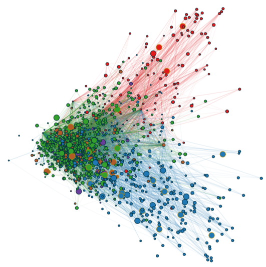
(c) April, 2009



(d) May, 2010



(e) November, 2011



(f) July, 2013

Figure 5.2: **Tail-Dependence Network Structure**
Figure 5.2 plots the pairwise linkage routes between two financial institutions, drawn in network plots using the multidimensional scaling algorithm which is scaled according to the relative distance between nodes. Each link represents risk spillovers as measured by network $\Delta CoVaR$.Nodes are colored by country groups, and links are colored according to the corresponding origin nodes: blue – United States, brown – Eurozone, purple – China, red – Japan, green – rest of the world.Individual plots are available in Figures 5.13-5.18.

Evolution of Topology Measures

How the global tail dependency network structure evolves over time is measured by network centrality measures of degree and closeness. Figure 5.3 plots these measures in the sample period by country and measure type and Table 5.4 reports the summary of values averaged in different phases in the sample periods. Degree denotes the total number of links both originating from a node and received by a node, which represents the overall connectedness of an institution. Closeness denotes the average length of steps for a node to reach a random node in the network, and lower levels of closeness implies contagion effects are propagated more rapidly throughout the network from originator node to a random node. These two measures complement each other as degree measures to what extent a node is directly connected and closeness represents the centrality of a node with its direct and indirect connections.

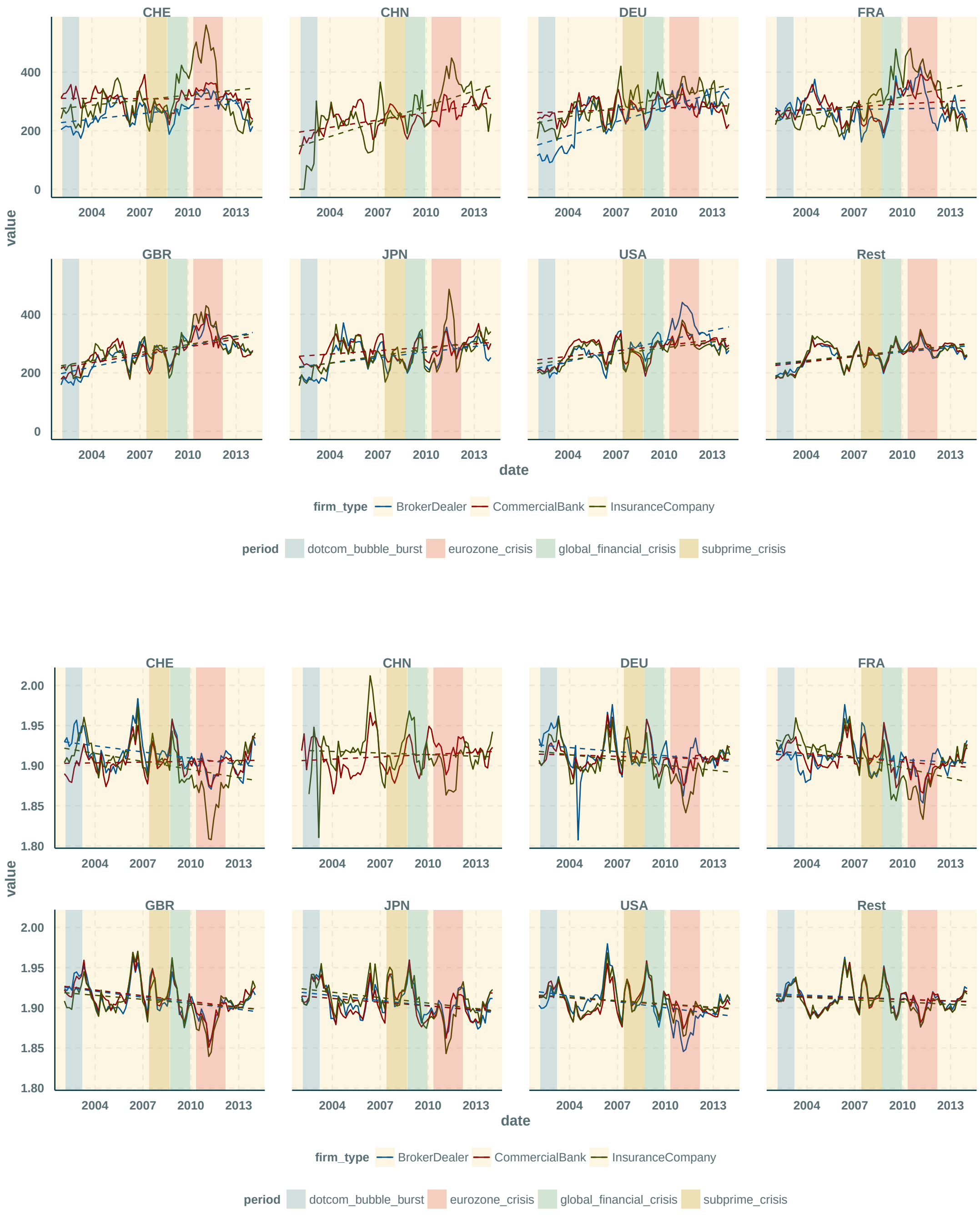


Figure 5.3: **Network Topology Measures** – Top: Degree Centrality, Bottom: Closeness Centrality

Table 5.4: **Entities for Sovereign Banking Sector Equity**

Table 5.4 reports network topology measures of degree centrality, and closeness centrality, grouped by countries, financial sectors, and time periods. Degree refers to the total number of links a node has both as an originator and as a receiver, and closeness denotes the average steps for a node to reach a random node in the network. For degree, the “Others” columns are formatted as “X, Y” where X denotes the proportion of connections with respect to nodes in other countries, and Y denotes the proportion of connections with respect to nodes in the United States.

Country	Broker-Dealers			Commercial Banks			Insurers		
	Degree		Closeness	Degree		Closeness	Degree		Closeness
	Total	Others		Total	Others		Total	Others	
Whole Sample Period									
CHE	277.62	0.97, 0.30	1.91	306.55	0.96, 0.33	1.91	330.60	0.96, 0.28	1.89
CHN	-	-	-	263.63	0.98, 0.31	1.91	295.25	0.99, 0.30	1.91
DEU	288.73	0.98, 0.31	1.91	277.66	0.98, 0.29	1.91	323.48	0.98, 0.31	1.90
FRA	276.66	0.98, 0.29	1.91	293.14	0.96, 0.29	1.90	339.27	0.97, 0.28	1.89
GBR	298.35	0.95, 0.31	1.90	292.63	0.95, 0.31	1.91	303.64	0.95, 0.31	1.90
JPN	267.12	0.82, 0.29	1.90	281.22	0.81, 0.29	1.90	278.44	0.82, 0.29	1.90
USA	318.50	0.61, 0.39	1.90	290.16	0.62, 0.37	1.91	285.51	0.61, 0.38	1.90
Rest	272.54	0.98, 0.31	1.91	275.76	0.97, 0.31	1.91	275.87	0.98, 0.31	1.91
June, 2007 - September, 2008									
CHE	259.67	0.97, 0.28	1.92	282.61	0.97, 0.35	1.91	261.41	0.97, 0.23	1.91
CHN	-	-	-	264.82	0.98, 0.31	1.89	248.19	0.99, 0.28	1.91
DEU	268.60	0.98, 0.26	1.91	266.65	0.98, 0.28	1.92	312.91	0.98, 0.27	1.92
FRA	219.38	0.98, 0.27	1.91	239.00	0.97, 0.31	1.92	292.09	0.98, 0.27	1.90
GBR	262.28	0.95, 0.28	1.92	249.30	0.94, 0.30	1.92	274.91	0.94, 0.28	1.92
JPN	234.87	0.86, 0.29	1.92	248.58	0.83, 0.30	1.92	236.72	0.87, 0.27	1.92
USA	268.16	0.61, 0.38	1.91	255.43	0.63, 0.36	1.92	251.16	0.61, 0.38	1.91
Rest	252.37	0.97, 0.30	1.92	256.80	0.97, 0.29	1.92	251.02	0.98, 0.31	1.92

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Table 5.4 – *Continued from previous page*

Country	Broker-Dealers			Commercial Banks			Insurers		
	Degree		Closeness	Degree		Closeness	Degree		Closeness
	Total	Others		Total	Others		Total	Others	
September, 2008 - December, 2009									
CHE	249.97	0.96, 0.27	1.92	287.91	0.96, 0.31	1.91	348.66	0.96, 0.25	1.90
CHN	-	-	-	220.68	0.98, 0.31	1.91	269.75	0.99, 0.31	1.93
DEU	261.98	0.98, 0.31	1.92	282.15	0.98, 0.29	1.92	335.59	0.98, 0.33	1.90
FRA	283.71	0.98, 0.29	1.92	290.88	0.96, 0.26	1.91	377.62	0.96, 0.25	1.88
GBR	280.45	0.95, 0.29	1.91	265.98	0.95, 0.30	1.91	264.01	0.95, 0.28	1.91
JPN	269.92	0.87, 0.33	1.91	275.72	0.86, 0.33	1.90	265.06	0.87, 0.30	1.91
USA	294.61	0.66, 0.34	1.91	262.05	0.66, 0.33	1.92	273.36	0.65, 0.35	1.92
Rest	267.19	0.98, 0.30	1.91	264.45	0.97, 0.30	1.91	273.71	0.98, 0.30	1.91
December, 2009 - May, 2010									
CHE	280.83	0.96, 0.28	1.91	329.45	0.96, 0.34	1.90	394.62	0.96, 0.25	1.88
CHN	-	-	-	224.65	0.98, 0.33	1.95	223.00	1.00, 0.26	1.91
DEU	290.08	0.98, 0.33	1.92	291.50	0.99, 0.30	1.91	323.88	0.99, 0.34	1.90
FRA	341.42	0.97, 0.29	1.91	326.25	0.96, 0.28	1.91	400.50	0.96, 0.27	1.88
GBR	317.48	0.94, 0.32	1.91	305.40	0.94, 0.34	1.91	314.36	0.93, 0.30	1.90
JPN	213.67	0.68, 0.26	1.90	236.22	0.69, 0.25	1.89	204.12	0.69, 0.23	1.89
USA	305.83	0.59, 0.40	1.90	297.23	0.62, 0.37	1.92	273.91	0.60, 0.39	1.91
Rest	282.49	0.98, 0.32	1.92	265.50	0.97, 0.32	1.92	271.85	0.98, 0.32	1.91

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Table 5.4 – *Continued from previous page*

Country	Broker-Dealers			Commercial Banks			Insurers		
	Degree		Closeness	Degree		Closeness	Degree		Closeness
	Total	Others		Total	Others		Total	Others	
May, 2010 - March, 2012									
CHE	317.47	0.96, 0.30	1.89	342.68	0.96, 0.31	1.89	453.50	0.96, 0.30	1.85
CHN	-	-	-	265.08	0.98, 0.32	1.92	353.29	0.99, 0.33	1.89
DEU	307.44	0.98, 0.34	1.90	292.54	0.98, 0.28	1.90	337.81	0.98, 0.30	1.87
FRA	329.38	0.97, 0.29	1.89	360.74	0.95, 0.27	1.89	411.50	0.96, 0.27	1.87
GBR	351.04	0.95, 0.32	1.89	340.35	0.94, 0.32	1.89	374.86	0.94, 0.32	1.88
JPN	274.34	0.77, 0.28	1.90	282.16	0.77, 0.27	1.90	302.02	0.77, 0.29	1.89
USA	388.45	0.59, 0.41	1.87	321.12	0.60, 0.39	1.90	320.61	0.59, 0.40	1.89
Rest	288.92	0.98, 0.32	1.90	292.65	0.97, 0.31	1.90	295.29	0.98, 0.33	1.90
March, 2012 - February, 2014									
CHE	271.36	0.98, 0.32	1.90	299.62	0.97, 0.34	1.91	242.12	0.97, 0.30	1.91
CHN	-	-	-	299.70	0.98, 0.31	1.92	301.08	0.98, 0.28	1.92
DEU	302.40	0.99, 0.32	1.91	266.53	0.99, 0.32	1.91	314.13	0.99, 0.32	1.91
FRA	254.17	0.98, 0.31	1.91	265.21	0.98, 0.32	1.91	268.23	0.98, 0.33	1.91
GBR	283.89	0.96, 0.32	1.91	293.53	0.96, 0.32	1.91	282.83	0.95, 0.32	1.91
JPN	289.53	0.83, 0.28	1.89	315.05	0.81, 0.28	1.90	306.71	0.83, 0.30	1.91
USA	305.32	0.60, 0.40	1.90	304.08	0.62, 0.37	1.90	286.44	0.62, 0.38	1.90
Rest	274.67	0.98, 0.31	1.91	283.18	0.97, 0.31	1.91	277.71	0.98, 0.31	1.91

From the results we can observe that nodes become more connected during crisis phases, and the topology measures reach their peak values[9] not at the outbreak of the crises but towards the mid stages of the crisis which reflects the accumulation of market co-movement, though this behaviour varies by country and by financial sectors. The observed behaviour implies that the shifting of network structures are the consequences of extraordinary market movements by severe systemic distresses. Despite cyclical fluctuations and sector differences, there is a steady trend for greater interconnectedness in the global financial network, signifying deeper cross-border financial integration and greater globalised dependence among markets and sectors. On average, nodes would have about 300 direct connections with other nodes and the overall closeness in the network fluctuates around the value of 1.90 over different phases, suggesting that for nodes that are not directly connected (about 80% out of all nodes for our sample size), their relative distance is usually expected to be 1 step away from an immediate node. An external shock given such a level of closeness are expected to complete its propagation rapidly within 2 rounds, meaning that in order to prevent the damage of a large negative external shock from causing widespread damage in the global financial network, coordinated swift action from regulatory authorities are warranted.

For world average pattern excluding the specific countries in Figure 5.3, there are no clear distinctions among sectors, suggesting that from a world average perspective sector-wise differences of financial institutions are blurred from institutions providing cross-sector financial services. For countries with highly integrated financial markets, such as the United Kingdom (GBR) and the United States (USA), we also observe similar coordinated behaviour among sectors. In contrast, centrality measures of China (CHN) shift in greater span (especially for closeness) and the financial sectors have

[9] For closeness, peak values are represented as the "troughs" in the time series plot.

dissimilar behaviour. In addition, although there is a steady trend in the increase of direct connections, the trend for overall interconnectedness of institutions as measured by closeness stays relatively stable, whereas other countries have downward trending closeness measure. These results suggest that China's financial sectors are relatively less integrated to others than those in other countries such as the UK or the US, resulting in greater individual level heterogeneity and sector level heterogeneity. Since closeness is an overall indicator of interconnectedness by taking into account indirect connections, China's less integrated financial market is yet to reach the same level of interconnectedness as those in other markets.

For country-specific and sector-specific patterns, we observe that for Switzerland (CHE), China (CHN), and Japan (JPN), the insurance sectors have greater responses to crisis episodes, which is in line with the findings of Billio, Getmansky, Lo and Pelizzon (2012) and Ahelegbey (2015) that insurance sector could be more important sources of interconnectedness than other sectors. However, this is not the case for United States (USA) where commercial banks and insurers behave in similar patterns, but Broker-Dealers are more sensitive during the Eurozone Crisis period. This could be attributed to the fact that since the initial triggering events for Global Financial Crisis occur within the broker-dealer sector (the distress of Bear Sterns, Merrill Lynch, and Lehman Brothers), the sector as a whole is more sensitive to negative market sentiment in later periods. The patterns from specific countries and world average show that markets become more sensitive during the Eurozone Crisis episode when compared to earlier periods. Compared with earlier crises, there were several waves of negative shocks about sovereign countries fiscal distress spanning over a longer time horizon, resulting in markets stay in high volatility status without being able to start recovering before another distress signal was triggered, whereas in earlier crises, distress signals usually clustered around a shorter time horizon. In addition, Table 5.4 shows that for nodes in the United States and Japan, their foreign connections are lower than that of the nodes in other countries and world average level, which supports the evidence from 5.2 where nodes from these two countries have less foreign influence (both as originators and receivers) and form their distinctive clusters within the financial network. In the context of financial interconnectedness, we provide evidence of the US financial system as a dominating source of external influence for other markets, and the Japanese financial system as an example of a relative close system.

Overall we find that financial institutions become more connected to each other directly or indirectly during financial crises, whether this increase of connectedness will strengthen the robustness of the financial network through diversification or will destabilise the financial network remains to be examined in Section 5.6.

Distributions of Node Degrees

A small-world network is a type of network which has a fat tailed degree distribution, so that "hubs" exist in the structure providing connections to most of the nodes, and nodes are typically not directly linked but indirectly connected via these "hubs". Scale-free networks whose degree distributions follow power-law distributions are typical examples of small-world. The existence of scale-free network are found in large and complex network structures from social networks and web page cross-links (Muchnik, Pei, Parra, Reis, Andrade Jr, Havlin and Makse, 2013), to interbank markets in different countries (Boss, Elsinger, Summer and Thurner, 2004; Bech and Atalay, 2010; Cont et al., 2013). This phenomenon of linkage distributions could potentially exist only in a range of the overall distribution. The study of Clauset et al. (2009) shows that, in real world examples, there often exists a range of the data distributions that follows a power-law distribution (usually above the lower tail), and when such a behaviour exists, fitting the entire distribution with a least-square linear fit would fail to detect the existence of the power-law distribution, and simply reject the tail power-law distribution would lead to an inaccurate representation of the data. Following Clauset et al. (2009), we examine whether the degree distributions could potentially follow a power-law distribution in the form of

$$Pr(K >= k) = \frac{\alpha - 1}{k_{min}} \left(\frac{k}{k_{min}} \right)^{-\alpha}$$

where k_{min} is the lower bound minimum degree above which the empirical sample will be included in the fitting process. The lower bound is iteratively determined to provide the best fit from a Kolmogorov-Smirnov (KS) goodness-of-fit test, against the null hypothesis that the empirical distribution comes from the reference distribution (in this case, a power-law distribution).

In Figure 5.4 we plot the distributions of degrees in different time periods in a log-log scale, as well as the power-law fits suggested by the KS tests, with the summarised results in Table 5.5. In Table 5.5, KS tests consistently yield p-values above 0.1 in all periods considered, suggesting that the hypothesis of the empirical distribution coming from the proposed distribution cannot be rejected, which confirms the existence of power-law distributions in the tail-dependence networks. The general findings regarding the distribution of degrees show that, although the existence of pairwise links between individual institutions may vary in different time periods, the overall statistical topology of tail dependency network structure remains stable over time, which is that among the highly interconnected institutions, the top most interconnected institutions contribute to most of the linkages.

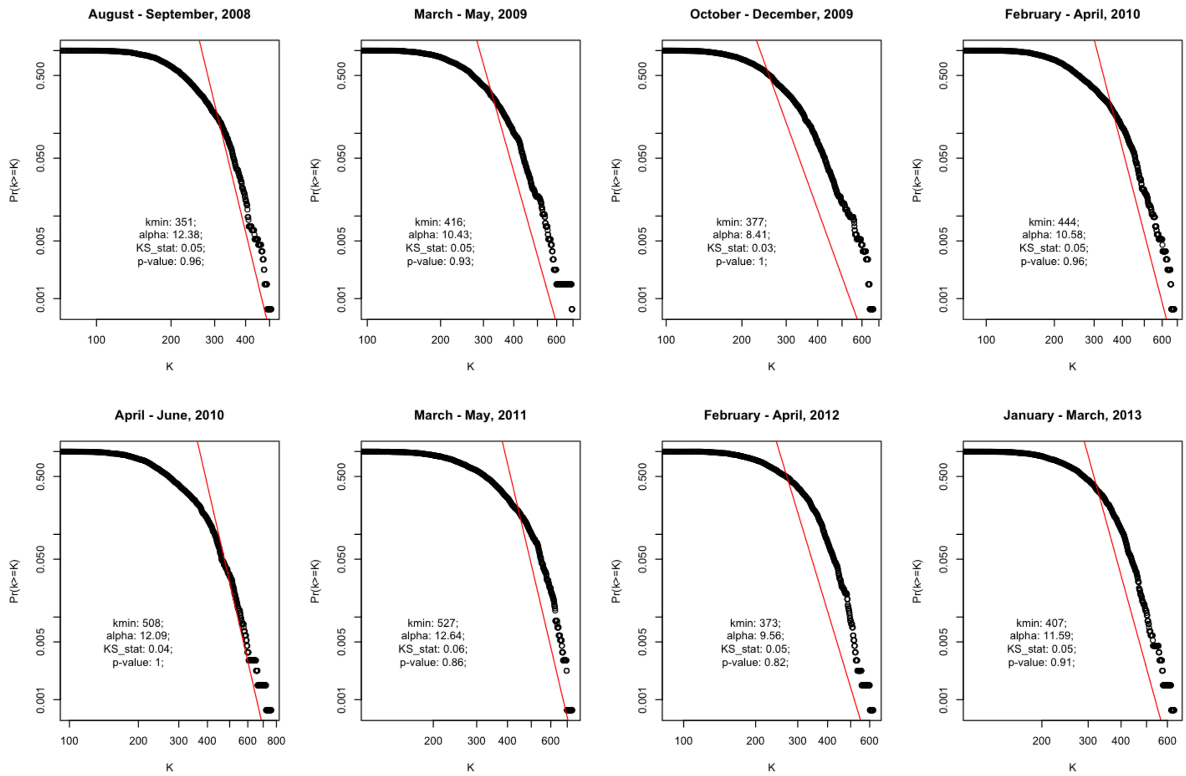


Figure 5.4: **Degree Centrality Distributions**

Table 5.5: **Summary of Degree Distribution Statistics**
Table 5.5 reports centrality measures and Kolmogorov-Smirnov (KS) test statistics, summarised by average over the different time periods. For definitions of density and centrality measures, please refer to Section 5.3.1. Statistic α is the fitted scaling parameter in power-law distribution denoting the rarity of events, statistic D is the two-sample KS test statistic with the null hypothesis of identical distribution for the two samples.

Period	Density	Centrality Measures		KS test statistics			
		Eigenvector	Degree	$\hat{\alpha}$	D	p	$P(p \geq 0.1)$
June, 2007 - September, 2008	0.09	0.39	249.2	10.80	0.04	0.96	1.00
September, 2008 - December, 2009	0.10	0.41	261.1	9.62	0.05	0.82	1.00
December, 2009 - May, 2010	0.10	0.37	272.5	9.13	0.05	0.96	1.00
May, 2010 - March, 2012	0.11	0.41	301.6	14.09	0.06	0.93	1.00
March, 2012 - February, 2014	0.10	0.45	279.8	10.93	0.05	0.91	1.00

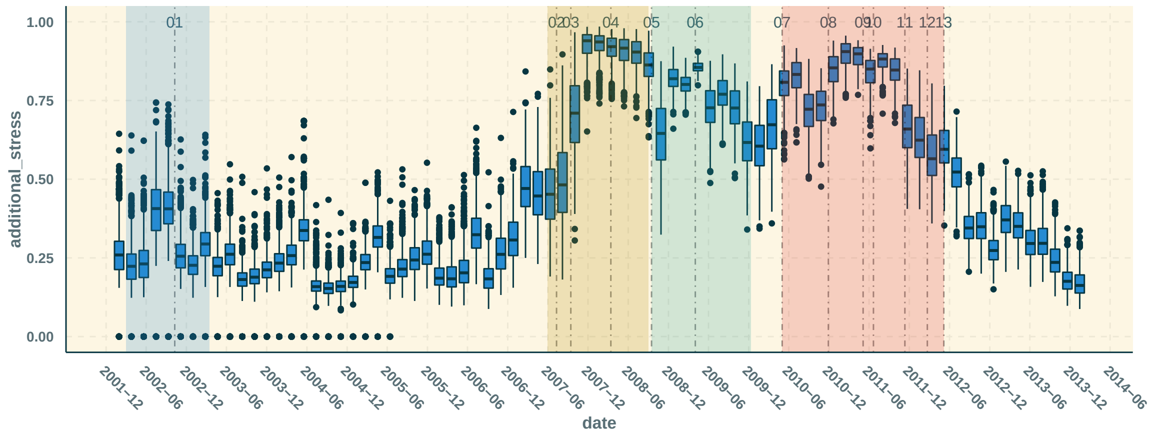
We observe that the structures of the tail-dependence network exhibit the scale-free small-world network property, as the distributions of degrees follow power-law distributions in the upper tails. The lower bounds for degree to be included in power-law is distributions in the upper tail of the empirical distributions, and that the scaling parameter α is around 10, suggesting that for a two-fold increase in degree, the large event is $(1/2)^{10}$ as likely as the smaller event, implying the existence of heavy upper tails far from the means of the whole distribution sample, and these upper tails typically follow power-law distributions. These findings in constructed tail-dependence networks are similar to the findings in previous studies regarding interbank lending markets in Cont et al. (2013) with the Brazilian data, and Boss et al. (2004) with the Austrian data, however in our case the power-law behaviour exists only deeper into the tails with a heavier decaying parameter. In this kind of networks, linkages are typically clustered within a few nodes, and two random nodes are usually connected to each other by indirect links via the most interconnected nodes. In the context of financial markets, contagion of the initial local distresses are typically propagated by the interconnection routes in the network structure, causing amplified losses spread to a wider range of institutions.

5.6 Network Impact from Interconnectedness Risk

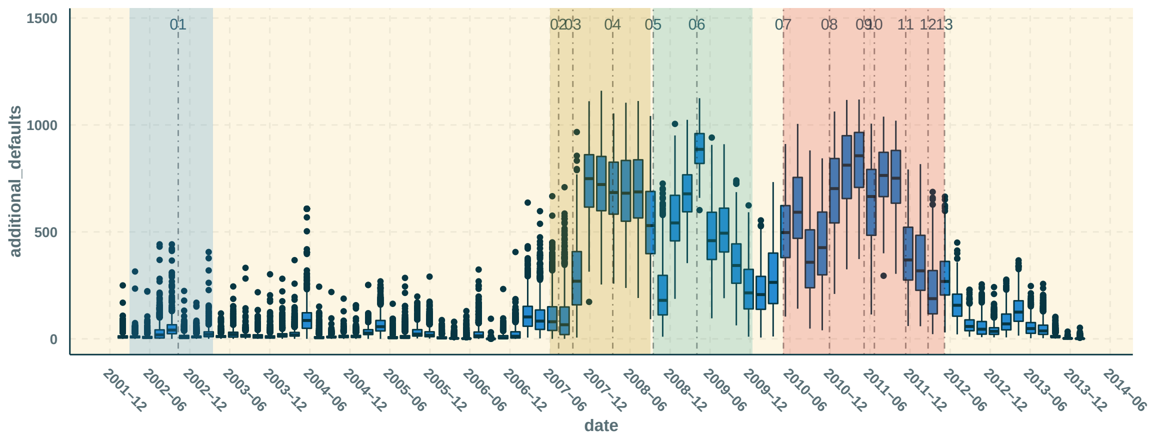
In order to study the impact of network interconnectedness to the resilience of the financial system, we assess the counterfactual economic losses as well as additional defaults caused by the subsequent risk propagation following the initial distress of an institution, using the DebtRank method described in Section 5.3.2. Specifically, for each adjacency matrix and impact matrix constructed for the rolling window snapshots, we calculate the network stresses induced by institution i's failure r_i as well as the weighted aggregate network stresses of random failures R, so that we can obtain a holistic view regarding the resilience of tail dependency network from interconnectedness impact.

5.6.1 Systemic Spillovers and Network Impact

Figure 5.5 plots the distributions of network stresses and defaults over the sample period, and Table 5.6 reports the network impact results aggregated over different crisis periods. Our results depict the surges of network stresses during the height of financial crises and the subsequent declines afterwards, which fit well with the major events occurred during the four crisis periods recorded in Table A.1. Financial crises lead tail dependence of the returns of financial institutions to become highly synchronised, with the evidence that the distributions of realised network impact become narrower in the peak periods of crises. Whereas in other periods, the distributions of network impact contain more idiosyncrasy of individual institutions in the form of outliers. Before the crisis periods in the later half of the sample period, network impact is generally low among institutions, and does not induce widespread defaults in the financial network. However, it is worth noting that although stresses induced by the failure of individual market participants are similar, the amount of potential defaults (the economic values of node drop to zero) vary significantly from individual basis. It is plausible that similar levels of stresses are realised in two scenarios: a more interconnected origin node inflicting less initial systemic spillovers, or a less interconnected origin node inflicting more initial systemic spillovers, with the latter case resulting in more defaults than the first case. This evidence supports the argument in Acemoglu et al. (2015) that whether network interconnectedness can serve as a mechanism for risk diversification depends on whether the initial impact is below or above a critical threshold.



(a) Additional Stresses



(b) Additional Defaults

Figure 5.5: **Aggregated Network impact**
Figure 5.5 plots the distributions of individual network impact in box plots. Graph (a) plots the distributions of network stresses (proportional to the economic value of the financial network) whereas Graph (b) plots the distributions of the number of network defaults originated from an individual stress events. Different crisis periods (as shown in shaded areas) and dates of major events are marked on the plots. Please refer to Table A.1 for specific definitions.

Table 5.6: **Evolution of Network Impact – Aggregated**
Table 5.6 reports the evolution of network induced impact, as measured by the overall losses of economic values, and the number of defaults of financial institutions. Values of mean, first quartile and third quartile are provided. Please refer to Figure 5.6 for a complete overview of the evolution of value distributions over time.

Period	Stress		Defaults	
	Mean	Range	Mean	Range
	Subprime Crisis			
January, 2007 - March, 2007	0.48	(0.41 - 0.54)	117.86	(59.00 - 152.00)
May, 2007 - July, 2007	0.46	(0.37 - 0.53)	105.85	(39.25 - 150.00)
December, 2007 - February, 2008	0.93	(0.91 - 0.96)	720.23	(599.00 - 852.75)
June, 2008 - August, 2008	0.90	(0.87 - 0.94)	700.92	(565.25 - 837.00)
	Global Financial Crisis			
August, 2008 - September, 2008	0.86	(0.83 - 0.90)	544.86	(398.25 - 689.00)
March, 2009 - May, 2009	0.86	(0.84 - 0.87)	893.02	(820.00 - 959.75)
May, 2009 - July, 2009	0.73	(0.68 - 0.78)	485.32	(371.00 - 591.75)
October, 2009 - December, 2009	0.62	(0.56 - 0.68)	238.25	(140.00 - 324.75)
	Crisis Aftermath			
December, 2009 - February, 2010	0.61	(0.54 - 0.67)	221.17	(138.00 - 292.00)
February, 2010 - April, 2010	0.67	(0.60 - 0.75)	287.47	(165.00 - 401.00)
	Eurozone Crisis			
June, 2010 - August, 2010	0.83	(0.79 - 0.87)	605.70	(470.00 - 754.75)
January, 2011 - March, 2011	0.90	(0.87 - 0.93)	796.89	(656.00 - 949.75)
December, 2011 - February, 2012	0.63	(0.57 - 0.70)	352.26	(227.00 - 484.00)
	Crisis Aftermath			
April, 2012 - June, 2012	0.60	(0.55 - 0.65)	283.38	(205.00 - 362.00)
July, 2013 - August, 2013	0.31	(0.26 - 0.34)	47.96	(21.00 - 64.00)
December, 2013 - February, 2014	0.17	(0.14 - 0.20)	1.88	(0.00 - 2.00)

Figure 5.6 plots the comparison among the initial risk spillovers, additional systemic stresses, and the amount of defaults over time, as averaged by institution's weights (total market value in the context of our study) at the time period. As shown in the Figure 5.6, the network impact is amplified tremendously by the initial impact due the failure of individual entities, with each of the affected institutions suffering the partial impact of the originator. The crisis periods are characterised by heavy losses of equity values and high number of default. It is only until when the Eurozone Sovereign Crisis coming to its end with the resolution of the second bailout package for Greece does the network stresses starts to fully decline and revert to the

pre-2007 level. The results from the impact analysis show that network impact to the system is largely influenced by three factors: the size of the initial impact, the interconnectedness of nodes that are potentially affected, and the specific routes via which the risk propagation is realised.

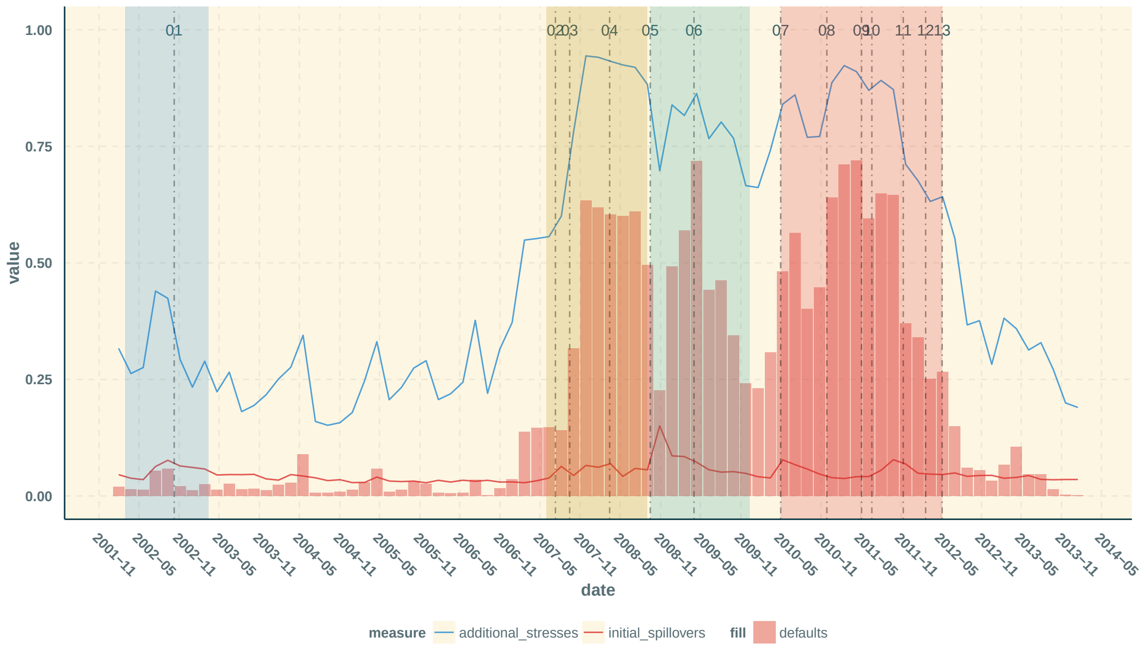


Figure 5.6: **Aggregated Network impact**
Figure 5.6 plots the evolutions of aggregated initial risk spillovers (measured as systemic $\Delta CoVaR$) and the subsequent network stresses (measured as DebtRank stresses). Series are averaged by individual weights in the system. Values are proportional to the total economic value of the financial system. Weighted average numbers of total defaults of financial institutions are shown as shaded bars.

Firstly, high initial severity from crises results in greater number of subsequent defaults. The three greatest levels systemic risk spillovers occur during Global Financial Crisis (November 2008 after the collapse of Lehman Brothers and Merrill Lynch) and Eurozone Financial Crisis (May 2010 first bailout of Greece, December 2011 distress for Italian Government Bond), and all of three events are accompanied by high levels of counterfactual defaults. With spillover impact at its highest levels, more institutions are prone to default due to the size of the impact. Since level of spillover impact during the peak periods of financial crisis is often accompanied by the increase in interconnectedness and clustering behaviour of nodes, network stresses are also at highest levels.

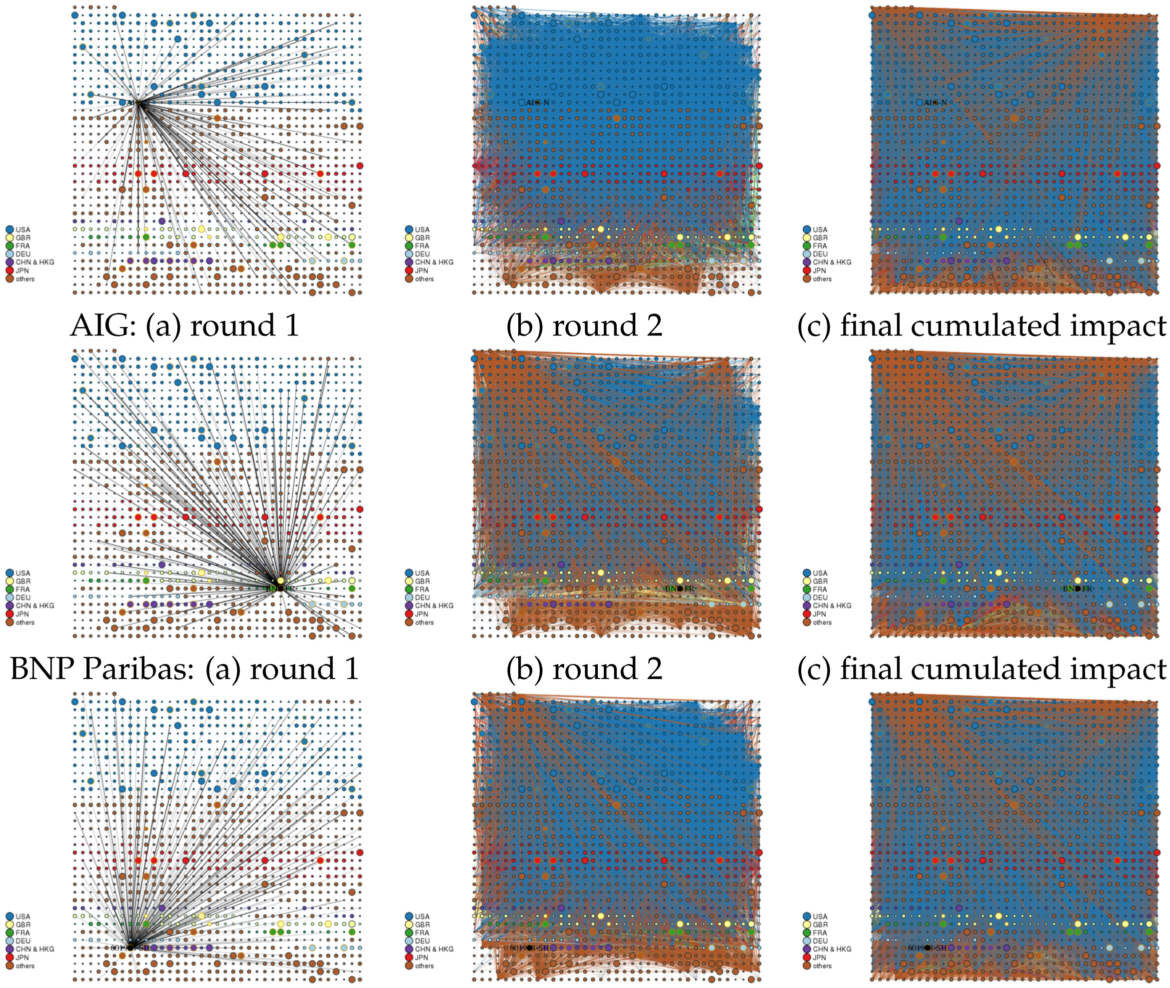
Secondly, network impact during crisis periods is characterised by the fact that it generally peaks some time after the starting point of crisis, but not immediately after the greatest impact. The Systemic spillovers peaked at the beginning of the Global Financial Crisis in November 2009, whereas the network stresses start to climb up and peak around April 2009. It can be attributed to that continuing increase in common interconnectedness as documented by the results of network centrality measures in Figure 5.3 in the previous section. With the crisis signal triggered in the United States, equity markets in other countries were also affected within a short time span of weeks and this cross-border contagion resulted in more institutions prone to negative market sentiment which increased the interconnectedness within and between sectors and markets. Greater common interconnectedness makes it more likely for the shock of initial impact to be transmitted to more directly connected neighbours, and easier for the shock to reach more indirectly connected nodes in shorter steps, which results in heavy losses to the system.

Thirdly, contrasting with two other crises, although its impact being severe, the severity duration of Global Financial Crisis is relatively short, as the increase in tail-dependence interconnectedness is temporary. It can be argued that during the Subprime Crisis the negative market sentiment is consistently concentrated in the credit risk of the individual institutions that engage in the subprime mortgage market in the US and the UK, therefore the risk spillover relationships are stable and so are the network stresses. The Eurozone Sovereign Crisis is characterised by the fact that market sentiment is shocked by several waves of negative signals from different area in the network about fiscal unsustainability of Eurozone countries. Market sentiment barely starts to recover before another wave of distress is realised, which further increases the connectedness level in all sectors and countries as evidenced in Figure 5.3 in the previous section, and it results in the highly severe and volatile network stresses during the Eurozone Crisis. In contrast, in Global Financial Crisis, there is arguably a single negative event with widespread influence but it is mitigated by the bailout programs of governments of major economies and their coordinated effort (such as the US Troubled Asset Relief Program and the UK Bank Rescue Package in 2008, and the G20 stimulus package in April 2009) to support economic recoveries and distress alleviation. Therefore there is only a short term temporary additional increase in network interconnectedness during the Global Financial Crisis.

5.6.2 Network Stresses and Vulnerability of Individual Institutions

Evidence in the previous section demonstrates that the aggregate network impact of institutions correspond closely to the general market conditions. Here we discuss the evidence from the perspective of individual institutions.

Individual Contributions of Interconnectedness Risk



AIG: (a) round 1 (b) round 2 (c) final cumulated impact

BNP Paribas: (a) round 1 (b) round 2 (c) final cumulated impact

Bank of China: (a) round 1 (b) round 2 (c) final cumulated impact

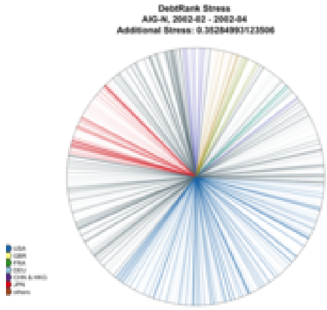
Figure 5.7: **Propagation of Network Stresses – April 2009**

Figure 5.7 plots the pairwise stress impact as 1) in initial risk spillovers, 2) in subsequent round, 3) final cumulated impact. Links in black represents initial risk spillovers as measured by $\Delta CoVaR$, and subsequent colored links represent the stresses induced by risk propagation. Nodes and links is colored by the country group of origin institutions.

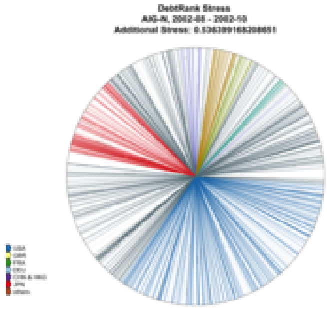
Figure 5.7 plots the propagation dynamics of network stresses of three financial institutions: American International Group (AIG), BNP Paribas and Bank of China, and their individual network stresses are reported in Figures 5.8, 5.9, and 5.10. Previous results in Figure 5.3 and Table 5.4 show a general closeness centrality of 1.9 meaning that on average risk spillovers will complete propagation within less than one more round after the occurrence of the initial risk spillovers. Evidence in Figure 5.7 shows the network stresses under strong interconnectedness and rapid propagation of risk spillovers. In the initial state, distress from the origin node i is transmitted to i's direct neighbours in the form of risk spillovers, then the network stresses are transmitted from i's neighbours to other indirectly connected nodes down the transmission routes, and given a highly interconnected tail dependency network, most of the nodes are affected, resulting in severe economic losses and defaults, as shown in the previous results of Figure 5.5.

Figure 5.8, Figure 5.9, and Figure 5.10 plot the coverage of stress impact from each of the aforementioned three institutions to their neighbouring institutions over specific time periods. Each plot places the institution of risk origin in the center while the rest of the institutions are placed in the periphery as a star graph, with each links measuring the existence and the strength of network stresses from the origin institution. A dense plot means the institution of interest will cause a high level of stresses among other institutions either directly or indirectly, whereas a scarce plot would mean a low level of impact.

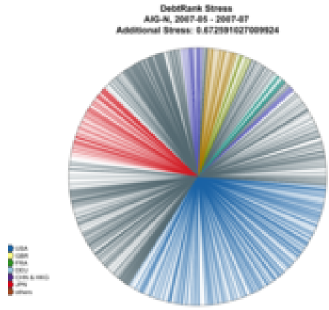
AIG faced a series of market stresses during the late Subprime Crisis to the early Financial Crisis period and was bailed out by US government in late 2008, the risk profile of which is also reflected in our results. Contrasting with the peaking of system-wide network stresses after the outbreak of Global Financial Crisis as shown in Figure 5.6, In Figure 5.8 AIG's network stresses peak in the first half of 2008, and our results show the evidence of alleviation of its market conditions over the Global Financial Crisis period. And AIG would be also less involved in the Eurozone Crisis when compared to the other two aforementioned banks. Network impact from BNP would peak at around early 2011 when market fear about the sustainability of Eurozone member states begin to spread from Greece to Italy and France. However as shown from earlier discussions, when market confidence began to restore, network impact steadily declines as both the severity of spillovers and the potential co-movement linkages begin to drop. It is also worth noting that for markets that are relatively less closely integrated to the central global financial markets, such as China in the early periods, network impact is also relatively smaller. However when the markets become more integrated by cross-border investment, international financial services, and counterparty transactions, individual institutions become more heavily influenced by market co-movement resulting in more integrated network structure, which in turn, might pose high network stress impact. The patterns of network stresses by other institutions also generally reflect the overall risk climate in the financial market, with their own minor idiosyncrasy in stresses and direct neighbours. Table 5.7 reports the top risk originators and receptors with regard to selected SIFIs, and their characteristics of size and network interconnectedness. We find that for these top risk originators and receptors, the measures of their sizes and interconnectedness are also in the highest percentiles, implying there is a clear connection between the network stress and the underlying sizes and interconnectedness. Table 5.14 reports the network stresses for other SIFIs over different periods in the study.



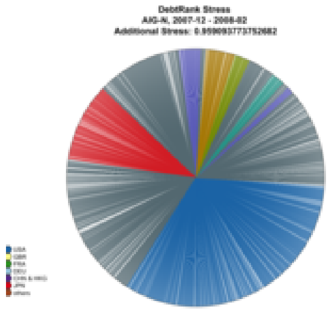
(a) February - April, 2002



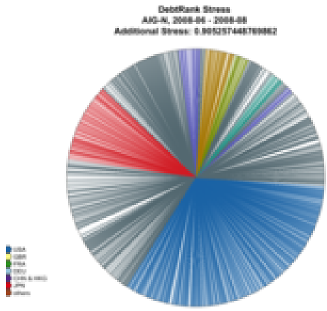
(b) August - October, 2002



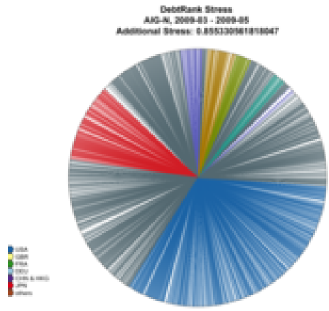
(c) May - July, 2007



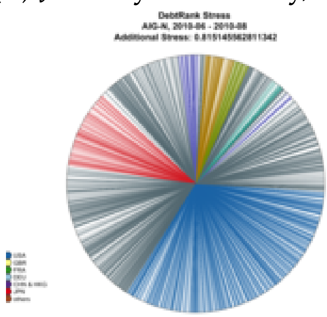
(d) January - February, 2008



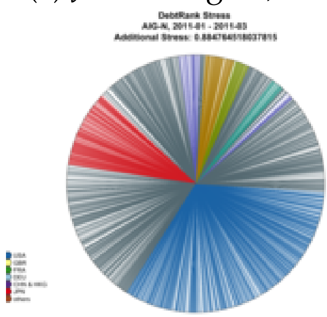
(e) June - August, 2008



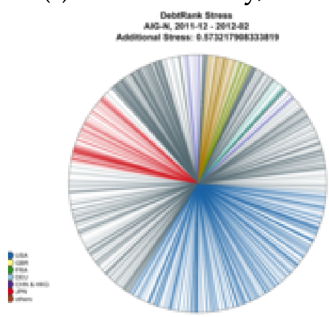
(f) March - May, 2009



(g) June - August, 2010



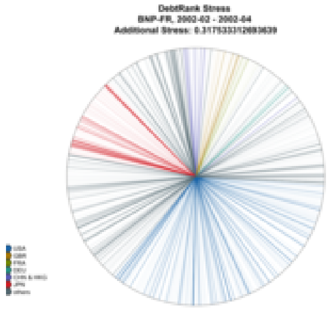
(h) January - March, 2011



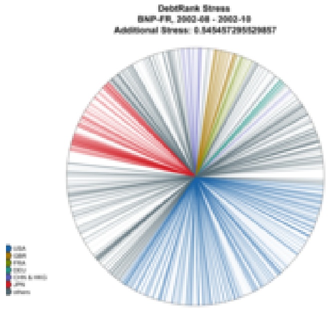
(i) December, 2011 - Februrary 2012

Figure 5.8: **Individual Network Stresses, Origin: American International Group (AIG)**

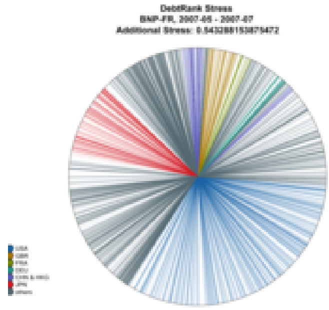
Figure 5.8 plots the directional network impact from an origin node to all other nodes that are affected by the origin, in a star graph layout. Each line depicts the network impact from the origin node to the target node, and the density of the plot represents the impact coverage and severity of the network impact from the origin node.



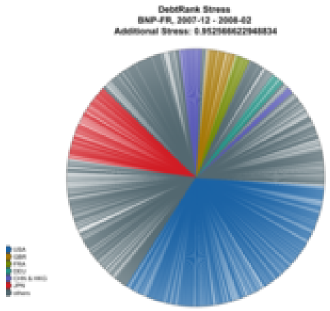
(a) February - April, 2002



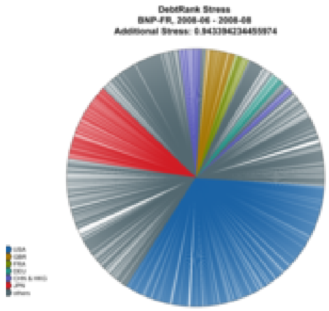
(b) August - October, 2002



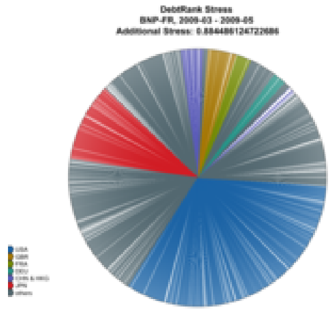
(c) May - July, 2007



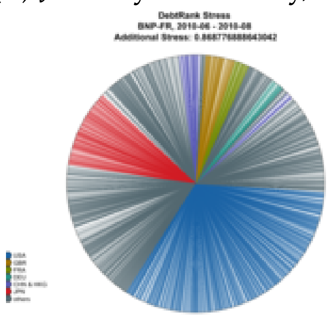
(d) January - February, 2008



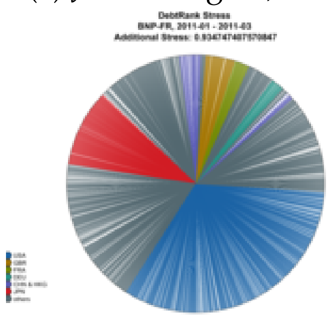
(e) June - August, 2008



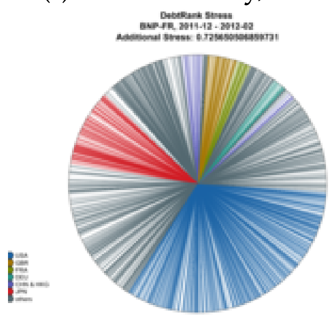
(f) March - May, 2009



(g) June - August, 2010

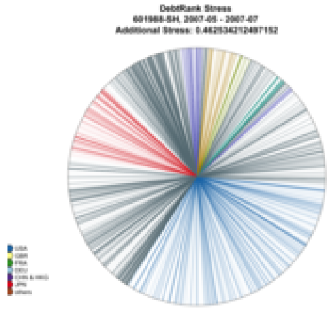


(h) January - March, 2011

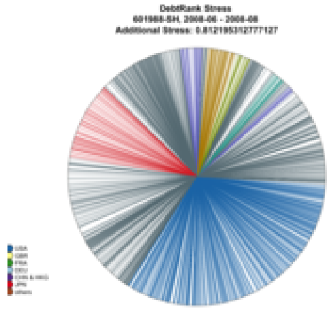


(i) December, 2011 - Februrary 2012

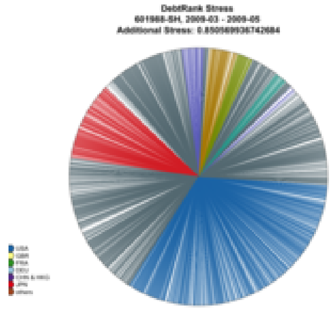
Figure 5.9: **Individual Network Stresses, Origin: BNP Paribas**
Figure 5.9 plots the directional network impact from an origin node to all other nodes that are affected by the origin, in a star graph layout. Each line depicts the network impact from the origin node to the target node, and the density of the plot represents the impact coverage and severity of the network impact from the origin node.



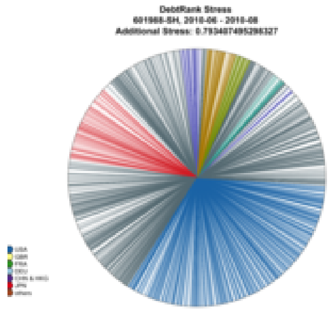
(a) May - July, 2007



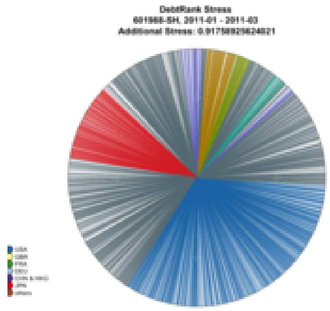
(b) June - August, 2008



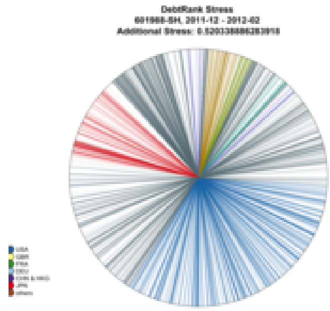
(c) March - May, 2009



(g) June - August, 2010



(h) January - March, 2011



(i) December, 2011 - Februrary 2012

Figure 5.10: **Individual Network Stresses, Origin: Bank of China**
Figure 5.10 plots the directional network impact from an origin node to all other nodes that are affected by the origin, in a star graph layout. Each line depicts the network impact from the origin node to the target node, and the density of the plot represents the impact coverage and severity of the network impact from the origin node.

Table 5.7: **Top Risk Originators/Receptors to/from Financial Institutions**
Table 5.7 reports the top 3 risk originators that contribute most to the distress of the specified financial institutions as well as top 3 risk receptors that are most affected by the distress of the specified financial institutions.We divide the periods into the Global Financial Crisis period ("period1") and European Financial Crisis period ("period2").Th measures of size, degree and closeness ("cl.") are reported as percentiles.

	top risk originators to $\{FI\}$					top risk receptors from $\{FI\}$				
period	from_id	stress	size	degree	cl.	to_id	stress	size	degree	cl.
FI: *601988-SH* (Bank of China)										
period1	INVE'B-SK	0.37	89	95	99	AGN-AE	1.00	93	94	100
	PKSVF-5	0.35	92	95	98	BNP-FR	1.00	100	97	100
	GBLB-BT	0.33	94	96	98	CS-FR	1.00	99	99	100
period2	AEL-N	0.30	54	99	49	ACA-FR	1.00	96	100	80
	INVE'B-SK	0.29	89	100	49	ALV-FF	1.00	99	100	92
	STB-OS	0.29	77	98	48	MS-N	1.00	97	100	89
FI: *AIG-N* (American International Group, Inc.)										
period1	GBLB-BT	0.96	94	96	98	ACA-FR	1.00	98	99	100
	L-N	0.96	93	90	97	AGN-AE	1.00	93	94	100
	MS-N	0.96	98	99	100	ALV-FF	1.00	99	97	100
period2	PWF-T	0.42	94	90	49	ACA-FR	1.00	96	100	80
	INVE'B-SK	0.40	89	100	49	ALV-FF	1.00	99	100	92
	STAN-LN	0.40	99	84	86	BAC-N	1.00	100	100	57
FI: *BNP-FR* (BNP Paribas)										
period1	2318-HK	1.00	96	85	99	ACA-FR	1.00	98	99	100
	601398-SH	1.00	100	18	99	AGN-AE	1.00	93	94	100
	601988-SH	1.00	100	15	100	ALV-FF	1.00	99	97	100
period2	2318-HK	1.00	96	94	56	2318-HK	1.00	96	94	56
	8306-TO	1.00	100	91	65	ACA-FR	1.00	96	100	80
	8316-TO	1.00	98	89	67	AGN-AE	1.00	91	100	79
FI: *HSBA-LN* (HSBC)										
period1	ACA-FR	1.00	98	99	100	ACA-FR	1.00	98	99	100
	AGN-AE	1.00	93	94	100	AGN-AE	1.00	93	94	100
	ALV-FF	1.00	99	97	100	ALV-FF	1.00	99	97	100
period2	8411-TO	1.00	97	70	63	2318-HK	1.00	96	94	56
	ACA-FR	1.00	96	100	80	ACA-FR	1.00	96	100	80
	AGN-AE	1.00	91	100	79	AGN-AE	1.00	91	100	79

Individual Vulnerability from Network Stresses

Figure 5.11 compares the network stresses that the Systemically Important Financial Institutions (SIFIs) impose on the network system with their vulnerabilities, i.e. the levels of network stresses that they receive from the defaults of other institutions. From the perspective of individual institutions, Figure 5.11 shows how the distress of the network system affects market participants during different stages of crisis periods. Before the outbreak of Subprime Mortgage Crisis, the stresses and vulnerabilities of institutions are in relatively low levels as compared to the crisis periods where institution-wise individual defaults can impose significant impact to the systems. Figure 5.11 also supports the previous findings in Figure 5.2 regarding the disaggregation of certain node groups to exposures of network impact, from the perspective of individual nodes. The several episodes of crisis impose heavy pressure to the risk positions of the SIFIs, especially to institutions in the western markets. However, market participants in China and Japan form their own node clusters as shown in Figure 5.2, so that they are less involved in the several crises originated from the US or the Eurozone.

Figure 5.11: **Vulnerability vs. Stresses of SIFIs**
Figure 5.11 plots the relative reverse ranks of initial spillovers (y-axis) and subsequent network stress (x-axis) of financial institutions.

Figure 5.12 plots the relationship of the initial risk spillovers and network stresses. Data points are grouped by stages of crisis in colour then by interconnectedness in subplots. The risk patterns of institutions correspond closely to the stages of crisis theory are in, suggesting the existence of the influence of a strong homogenous market co-movement force to the market participants, especially in the middle stages of crisis when market distress is most severe. This market force is more obvious in the Global Financial Crisis plots than the Eurozone Crisis plots with a greater clustering of data points. For institutions that are most interconnected (subplots 3 and 4), their linear fitted slopes are usually highly positive where a single increase in risk spillovers would result in large increase in network stresses, and this pattern is less clear for institutions that are least interconnected (subplots 1) which imply that the low linkages inhibit the propagation of risk spillovers. In addition, for Eurozone Crisis, there are greater distinctions between data points in different crisis stages, which supports the previous evidence in Figure 5.6, where there are at least two visible cycles of distress, which corresponds with the first round bailout of Greece and the later distress in Italy. Despite distinct features in risk patterns between the two crises, we observe a strong relationship between risk spillovers and network stresses when conditioning interconnectedness and crisis stages.

(a) Global Financial Crisis

(b) Eurozone Sovereign Crisis

Figure 5.12: **Initial Spillovers vs. Network Stresses**
Figure 5.12 plots the relative reverse ranks of initial spillovers (x-axis) and network stress (y-axis) of financial institutions. Data points are colored acccording to the contemporaneous stages of the sample period. Plots are grouped by the quartiles of quartiles of closeness centraity with subplot 1 containing institutions that are least interconnected and subplot 4 containing institutions that are most interconnected.

5.6.3 Contributions of Systemic Risk Spillovers and Interconnectedness to Network Stresses

We examine to what extent can network stresses induced by the failure of a institution be attributed to various factors representing the risk characteristics of financial institutions. We construct a panel regression model where the institution's network stresses is treated as the dependent variable. For explanatory variables we include the institution's size (of its market value), leverage level (book liability to equity ratio), and network centrality measures of closeness and degree. We further divide degree measures into the amount of outward, inward, and total connections (`in_connections`, `out_connections`, and `in_out_connections`), and the measures with respect to institutions in other financial sectors (`in_from_other`, `out_to_other`, and `in_out_other`). As for initial risk spillovers (`spillovers`), we also include its quadratic form (`spillovers2`), as well as the interaction term between spillovers and a dummy variable representing non-crisis periods (`spillovers_non_crisis`). The dependent variables and explanatory variables are log transformed so the fitted coefficients represent elasticities.

Table 5.15 reports the correlation matrix table for the variables used in the regressions in Table 5.8 to Table 5.11. As shown in Table 5.15, there are generally high correlations ($\rho_{i,j} \geq 0.7$) among the degree measures, and since the regressions are specified in a panel manner, the collinearity of degree measures in sub-groups is higher than the general pooled group, which leads to a multi-collinearity problem. We avoid the problem of multi-collinearity by using one form of degree measures at a time. Table 5.8 reports the main regression model results, where each model represents one form of degree measures. To account for heteroskedasticity and autocorrelation, we use Newey-West standard error estimates (up to 4 lags) for statistical tests.

Main Panel Model Results

Table 5.8: **Panel Regression Results on Network Stresses - Full Sample**
Table 5.8 reports the panel regression results for network stresses as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses.

	Dependent variable: `network_stresses`						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`spillovers`	-0.394^{***}	-0.394^{***}	-0.266^{***}	-0.383^{***}	-0.395^{***}	-0.330^{***}	-0.383^{***}
	(0.044)	(0.044)	(0.039)	(0.044)	(0.044)	(0.040)	(0.044)
`spillovers2`	-0.046^{***}	-0.046^{***}	-0.022^{***}	-0.044^{***}	-0.046^{***}	-0.034^{***}	-0.044^{***}
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
`spillovers_non_crisis`	0.103^{***}	0.103^{***}	0.184^{***}	0.111^{***}	0.103^{***}	0.154^{***}	0.111^{***}
	(0.015)	(0.015)	(0.011)	(0.014)	(0.015)	(0.012)	(0.014)
`size`	0.017^{***}	0.017^{***}	0.011^{***}	0.017^{***}	0.017^{***}	0.014^{***}	0.017^{***}
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
`lev`	0.001	0.001	-0.003	0.001	0.001	-0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
`closeness`	4.019^{***}	4.013^{***}	0.032	3.867^{***}	4.014^{***}	2.015^{***}	3.876^{***}
	(0.361)	(0.359)	(0.080)	(0.376)	(0.361)	(0.303)	(0.375)
`in_connections`		-0.002					
		(0.001)					
`out_connections`			0.379^{***}				
			(0.005)				
`in_out_connections`				0.026^{***}			
				(0.006)			
`in_from_other`					-0.003^{**}		
					(0.001)		
`out_to_other`						0.184^{***}	
						(0.011)	
`in_out_other`							0.023^{***}
							(0.005)
Observations	70,914	70,914	70,914	70,914	70,914	70,914	70,914
R^2	0.193	0.193	0.320	0.195	0.193	0.257	0.195
Adjusted R^2	0.189	0.189	0.314	0.192	0.189	0.252	0.191
Note:					*p<0.1; **p<0.05; ***p<0.01		

The results show that there is a non-linear concave down decreasing relationship between risk spillovers and network stresses, as the first order term and the second order term having both significant negative slopes. This suggests that the contemporary measures in network stress and risk spillovers exhibit a negative relationship, which is supported from their time series changes in Figure 5.6 where there are lagged responses in network stress from risk spillovers in general, except in peak crisis periods where the two measures move more synchronised[10]. We use a dummy representing non-crisis state (periods other than the crisis periods defined in Table A.1) to represent the severity of risk spillovers that is below a crisis state level. The interaction term between spillovers and non-crisis state shows also supports that as long as the severity of spillovers is in non-crisis state, increase in its severity will cause greater losses to other institutions in the network. However, when such severity surpasses the critical threshold, a very severe initial impact of risk spillovers by node i will cause outright defaults to some of i's direct neighbours. Although the defaults of some of i's neighbours create impact on their own, they will also prevent these nodes acting as intermediate "hubs" of risk propagation, which, since the nodes are only 1-2 steps away in the tail dependency network, reduces the impact from interconnectedness.

As for interconnectedness measures, the results show a high explanatory power for closeness, which represents the overall interconnectedness in the network. Closeness has the largest elasticity effect among all significant explanatory variables, as a 1% change in closeness can explain about 4% change in network stresses, in 4 out of 6 model formulations, suggesting that network stresses are very sensitive to the institutions' interconnectedness level. The explanatory power is partially shifted away from closeness when we use direct outward degree measures (model 3 and model 6), which is inline with the fact that direct connectedness plays an important role in the overall interconnectedness of nodes. In addition, the institutions' market-valued sizes are also accountable to network stresses, with elasticity effects of 0.011 - 0.017 across all formulations. As for other variables, there are minor negative effects for inward

[10] We discuss the explanatory powers of variables to the forward risk measures in Table 5.19.

degree measures (model 2 and model 5) but their fitted coefficients are close to zero, and we find no significant effects from the institutions' leverage levels and the fitted coefficient values are also close to zero.

Sub-samples and Forward Samples

Table 5.9: **Panel Regression Results on Network Stresses - Subprime and Global Financial Crises**
Table 5.9 reports the panel regression results for network stresses as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses. The sub-sample period is from September 2007 to July 2009.

	Dependent variable: network_stresses						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
spillovers	-0.133^{***}	-0.133^{***}	-0.079^{*}	-0.132^{***}	-0.133^{***}	-0.117^{**}	-0.132^{***}
	(0.051)	(0.051)	(0.045)	(0.050)	(0.051)	(0.046)	(0.050)
spillovers2	-0.026^{***}	-0.026^{***}	-0.018^{**}	-0.026^{***}	-0.026^{***}	-0.024^{***}	-0.026^{***}
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)
size	-0.001	-0.001	0.002	0.00002	-0.001	0.0002	-0.0002
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.004)	(0.006)
lev	-0.005	-0.005	0.003	-0.004	-0.005	-0.001	-0.004
	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.004)	(0.006)
closeness	1.940^{***}	1.935^{***}	-0.744^{***}	1.795^{***}	1.938^{***}	0.511^{***}	1.774^{***}
	(0.361)	(0.361)	(0.271)	(0.361)	(0.361)	(0.163)	(0.356)
in_connections		-0.002^{*}					
		(0.001)					
out_connections			0.271^{***}				
			(0.015)				
in_out_connections				0.027^{***}			
				(0.005)			
in_from_other					-0.002^{*}		
					(0.001)		
out_to_other						0.137^{***}	
						(0.006)	
in_out_other							0.028^{***}
							(0.004)
Observations	16,056	16,056	16,056	16,056	16,056	16,056	16,056
R^2	0.102	0.103	0.269	0.109	0.103	0.204	0.111
Adjusted R^2	0.094	0.094	0.246	0.100	0.094	0.186	0.102

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.10: **Panel Regression Results on Network Stresses - Eurozone Sovereign Crisis**
Table 5.10 reports the panel regression results for network stresses as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses. The sub-sample period is from May 2010 to May 2012.

	Dependent variable: `network_stresses`						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`spillovers`	0.307***	0.306***	0.322***	0.310***	0.305***	0.346***	0.313***
	(0.049)	(0.049)	(0.045)	(0.048)	(0.049)	(0.045)	(0.048)
`spillovers2`	0.059***	0.059***	0.064***	0.060***	0.059***	0.067***	0.061***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
`size`	0.005	0.005	0.005	0.005	0.006	0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
`lev`	−0.002	−0.001	−0.002	−0.002	−0.001	−0.002	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
`closeness`	1.559***	1.546***	0.217**	1.515***	1.545***	0.711***	1.511***
	(0.294)	(0.294)	(0.102)	(0.298)	(0.294)	(0.192)	(0.297)
`in_connections`		−0.003**					
		(0.001)					
`out_connections`			0.181***				
			(0.006)				
`in_out_connections`				0.012***			
				(0.004)			
`in_from_other`					−0.003***		
					(0.001)		
`out_to_other`						0.107***	
						(0.006)	
`in_out_other`							0.012***
							(0.004)
Observations	17,394	17,394	17,394	17,394	17,394	17,394	17,394
R^2	0.115	0.116	0.245	0.117	0.116	0.209	0.118
Adjusted R^2	0.106	0.107	0.226	0.108	0.107	0.193	0.108

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.9 and Table 5.10 report the regression results on the sample subsets[11] during the Subprime and Global Financial Crises (subset 1, September 2007 to July 2009) and the Eurozone Sovereign Crisis (subset 2, May 2010 to May 2012). The results

[11]We exclude risk spillovers' interaction term with non-crisis state in the crisis sub samples.

on subset 1 in Table 5.9 have similar pattern with our main results, where there is a non-linear concave down decreasing relationship between spillovers and network stresses. However, the network stresses are less sensitive to the changes in explanatory variables, as the marginal effects of these variables are dwarfed by the crisis state *per se*. In addition, size loses its explanatory powers in both periods of crisis. The distinctive results for subset 2 in Table 5.10 show that the slopes for risk spillovers are now concave upward increasing with greater elasticity coefficients than their equivalents in Table 5.8 and Table 5.9, implying that network stresses increase with risk spillovers throughout the sub-sample period in the Eurozone Sovereign Crisis. As discussed in Section 5.6.1, while the severity of the realised network stress around the Eurozone Sovereign Crisis is not as high as that during the outbreak of the Global Financial Crisis, the duration of market distress is longer since there are two major outbreaks in market distress (May 2010 and November 2011), which prevents the market recovering from a crisis state, and makes the financial institutions to respond to spikes in risk spillovers faster (which is typically a lagged response, as shown in Table 5.11).

Table 5.11: **Panel Regression Results on Network Stresses - Forward Measures**

Table 5.11 reports the panel regression results for network stresses (forward one quarter/year leads) as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses.

	Dependent variable: `network_stresses`								
	full sample			subset 1			subset 2		
	present	1 quarter	1 year	present	1 quarter	1 year	present	1 quarter	1 year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
`spillovers`	-0.652^{***}	-0.601^{***}	-0.314^{***}	-0.079^{*}	0.043^{**}	-0.070^{**}	0.318^{***}	0.835^{***}	-0.370^{***}
	(0.037)	(0.036)	(0.039)	(0.045)	(0.021)	(0.029)	(0.044)	(0.054)	(0.063)
`spillovers2`	-0.100^{***}	-0.091^{***}	-0.041^{***}	-0.018^{**}	0.006	-0.010^{**}	0.063^{***}	0.136^{***}	-0.055^{***}
	(0.006)	(0.006)	(0.006)	(0.008)	(0.004)	(0.004)	(0.007)	(0.009)	(0.010)
`size`	0.011^{***}	0.012^{***}	0.007^{***}	0.002	0.006^{*}	-0.0002	0.005	0.001	-0.005
	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
`lev`	-0.002	-0.004	0.001	0.003	-0.003	0.0002	-0.001	-0.003	-0.008^{*}
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
`closeness`	-0.044	0.042	0.016	-0.753^{***}	-0.037	0.181^{*}	0.175^{*}	-0.018	0.170^{**}
	(0.077)	(0.080)	(0.011)	(0.271)	(0.069)	(0.100)	(0.101)	(0.055)	(0.079)
`in_connections`	-0.010^{***}	-0.008^{***}	-0.001	-0.003^{***}	-0.003^{**}	0.003^{**}	-0.006^{***}	-0.004^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
`out_connections`	0.379^{***}	0.231^{***}	-0.021^{***}	0.271^{***}	0.130^{***}	-0.061^{***}	0.183^{***}	0.137^{***}	-0.028^{***}
	(0.005)	(0.005)	(0.004)	(0.015)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Observations	70,914	70,914	70,914	16,056	16,056	16,056	17,394	17,394	17,394
R^2	0.318	0.129	0.004	0.269	0.087	0.017	0.247	0.135	0.007
Adjusted R^2	0.304	0.111	-0.016	0.202	0.002	-0.074	0.184	0.062	-0.077

Note: *p<0.1; **p<0.05; ***p<0.01

In order to examine the forward explanatory powers of variables, we compare the contemporary specifications with forward specifications that are one quarter and one year in advance to the contemporary measures of the explanatory variables, for the full sample model as well as two subset sample models. Comparing Table 5.11 with previous results in Tables 5.8, 5.9, and 5.10, the one quarter models show comparable results with their contemporary models, but there are notable differences for the one-year model. Although the spillovers-stresses and interconnectedness-stresses relationships are stable for the full sample models, we find that during crisis periods, network topology for individual nodes changes frequently, resulting in the reversal of the relationships of spillovers/interconnectedness to network stresses between the one quarter model and the one-year model. In other words, the top contributors of systemic risk changes constantly, with each of these institutions imposing heavy systemic risk within a short time frame. This is reinforced by the evidence that closeness centrality in the previous periods has little power in explaining network stresses. In addition, we show that as crisis sub-samples, there is an evidence of lagged (about one quarter) responses from spillover effects to network stresses.

As robustness checks, we use the proportions of counterfactual defaults (`network_default`) as an alternative measure for network impact, where the results for contemporary models, subset models and forward models are shown in Tables 5.16 - 5.19. The variable coefficients and explanatory powers are similar to those in the main models, with the exception that the absolute values of the coefficients for risk spillovers are larger than those in the main models, which is not surprising given the previous results that the most severe impacts of risk spillovers make direct neighbours also default but eliminate their roles as network hubs as well. We believe our results of explaining network impact (defined by either counterfactual losses or defaults) using institutions' risk spillovers, interconnectedness are robust.

5.7 Conclusions

We study the tail-dependency network of the global financial system and explore its characteristics including the topological structures, and examine the network impact from the inherent interconnectedness risk. tail-dependence network is formed by the linkages of the tail distress events of financial institutions, which provides a propagation mechanism of systemic risk spillovers, and the interconnectedness of financial institutions is therefore an important source of systemic risk. Our results show that interconnectedness risk can inflict heavy losses to the financial system when the risk propagation can be fully realised. Therefore, regulators and policy-makers need to take into consideration the interconnectedness risk among financial institutions as a destabilising factor of financial stability as well as the network stresses when assessing the impact of a systemic event.

In terms of core results, we find that spillovers of the distress of one financial institution can be propagated to many institutions resulting in high level of interconnectedness among financial institutions, and the risk propagation due to interconnectedness results in greater level of losses than what is realised by the systemic impact of the initial distress. Adverse common market conditions of crisis not only exacerbate the impact of the initial distress, but create greater tail-dependence for the asset returns of financial institutions, making them vulnerable for the propagation of risk spillover effects. Therefore, network effect and interconnectedness risk lead to potential scenarios of market crash, if its effect can be fully realised. Our evidence regarding the tightening of interconnectedness during crisis periods is inline with the evidence documented in other studies regarding the interconnectedness of market series, such as Augustin (2012), Wang and Moore (2012) and Alter and Schüler (2012) for the CDS series and Billio, Getmansky, Lo and Pelizzon (2012) for the Granger-causality relationships of stock prices. Our results show that the heavy losses implied by the interconnectedness risk start to revert to the pre Subprime Crisis level after the second bailout package for Greece in March 2012. In this sense, our results justify the bailout packages and the efforts to restore market confidence and liquidity by the national and international authorities.

In addition, the impact of initial spillovers are shown to have a non-linear relationship with respect to network stresses, when initial impact increases above a threshold it leads to less realised network stresses as the defaults of some institutions, despite the impact of their own defaults, make them no longer able to propagate network stresses in the subsequent rounds. Our results also show that more heterogenous substructures inside the tail-dependency network are more resilient to adverse market conditions and network stresses, such as the financial markets of China and Japan. In this sense, our results are in favour of promoting a more diversified sector structure in the financial market and ring-fencing business exposures as it leads to a network structure with less interconnectedness and greater financial resilience.

Appendix 5.A Appendix

Table 5.12: **List of Global Systemically Important Banks**
Table 5.12 reports the definition of Global Systemically Important Banks (G-SIBs) referenced in this study. The G-SIBs definition and list of included institutions is provided by the 2015 update of Financial Stability Board (Financial Stability Board, 2015*a*). SEDOL (Stock Exchange Daily Official List) and One Banker Quote Symbol are the two symbols to identify institutions.

Name	SEDOL	Quote Symbol	Home Country
Agricultural Bank of China	B620Y41	601288-SH	China
BNP Paribas	7309681	BNP-FR	France
Bank of America	2295677	BAC-N	United States
Bank of China	B180B49	601988-SH	China
Bank of New York Mellon	B1Z77F6	BK-N	United States
Barclays	3134865	BARC-LN	United Kingdom
China Construction Bank	B0LMTQ3	939-HK	China
Citigroup	2297907	C-N	United States
Credit Suisse	7171589	CSGN-VX	Switzerland
Deutsche Bank	5750355	DBK-FF	Germany
Goldman Sachs	2407966	GS-N	United States
Groupe BPCE[1]	-	-	France
Groupe Crédit Agricole	7262610	ACA-FR	France
HSBC	0540528	HSBA-LN	United Kingdom
ING Bank	7154182	INGA-AE	Netherlands
Industrial and Commercial Bank of China Limited	B1G2JY3	601398-SH	China
JP Morgan Chase	2190385	JPM-N	United States
Mitsubishi UFJ FG	6335171	8306-TO	Japan
Mizuho FG	6591014	8411-TO	Japan
Morgan Stanley	2262314	MS-N	United States
Nordea	5380031	NDA'SEK-SK	Sweden
Royal Bank of Scotland	B7T7721	RBS-LN	United Kingdom
Santander	5705946	SAN-MC	Spain
Société Générale	5966516	GLE-FR	France
Standard Chartered	0408284	STAN-LN	United Kingdom
State Street	2842040	STT-N	United States
Sumitomo Mitsui FG	6563024	8316-TO	Japan
UBS	BRTR118	UBS-N	United States
Unicredit Group	B5M1SM3	UCG-MI	Italy
Wells Fargo	2649100	WFC-N	United States

[1] Groupe BPCE is not a public listed firm and so is not available in our study.

Table 5.13: **List of Global Systemically Important Insurers**
Table 5.13 reports the definition of Global Systemically Important Insurers (G-SIIs) referenced in this study. The G-SIBs definition and list of included institutions is provided by the 2015 update of Financial Stability Board (Financial Stability Board, 2015*b*). SEDOL (Stock Exchange Daily Official List) and One Banker Quote Symbol are the two symbols to identify institutions.

Name	SEDOL	Quote Symbol	Home Country
Aegon N.V.	5927375	AGN-AE	Netherlands
Allianz SE	5231485	ALV-FF	Germany
American International Group, Inc.	2027342	AIG-N	United States
Aviva plc	0216238	AV.-LN	United Kingdom
Axa S.A.	7088429	CS-FR	France
MetLife, Inc.	2573209	MET-N	United States
Ping An Insurance (Group) Company of China, Ltd.	B01FLR7	2318-HK	China
Prudential Financial, Inc.	2819118	PRU-N	United States
Prudential plc	0709954	PRU-LN	United Kingdom

Table 5.14: **Evolution of Network Impact - Individual Financial Institutions**

Table 5.14 reports the evolution of network induced impacts, as measured by the overall losses of economic values. The reported values are the averaged weekly values over an eight-week window around the specified months. For firm names of respective firm code please refer to Table 5.12 and Table 5.13.

Country	Firm Code	Feb, 07	Jan, 08	Jul, 08	Sep, 08	Apr, 09	Jun, 09	Jan, 10	Mar, 10	Jul, 10	Feb, 11	May, 12	Jul, 13
Switzerland	CSGN-VX	0.64	0.96	0.96	0.95	0.88	0.80	0.69	0.81	0.90	0.93	0.68	0.33
	UBS-N	0.58	0.96	0.96	0.94	0.88	0.81	0.74	0.80	0.88	0.93	0.70	0.34
China	2318-HK	0.68	0.96	0.89	0.84	0.87	0.77	0.75	0.77	0.87	0.94	0.62	0.26
	601988-SH	0.37	0.87	0.81	0.77	0.85	0.64	0.50	0.53	0.79	0.92	0.49	0.30
Germany	ALV-FF	0.60	0.95	0.94	0.90	0.88	0.83	0.75	0.79	0.89	0.95	0.76	0.32
	DBK-FF	0.66	0.95	0.94	0.94	0.88	0.79	0.66	0.75	0.85	0.94	0.71	0.37
France	ACA-FR	0.65	0.96	0.96	0.93	0.89	0.83	0.71	0.80	0.88	0.94	0.70	0.29
	BNP-FR	0.57	0.95	0.94	0.92	0.88	0.84	0.71	0.76	0.87	0.93	0.69	0.31
	CS-FR	0.66	0.95	0.95	0.95	0.89	0.83	0.76	0.80	0.88	0.94	0.71	0.40
United	HSBA-LN	0.57	0.95	0.93	0.91	0.87	0.82	0.66	0.74	0.85	0.92	0.70	0.29
Kingdom	PRU-LN	0.67	0.97	0.95	0.91	0.88	0.82	0.76	0.84	0.90	0.95	0.55	0.34
	STAN-LN	0.66	0.96	0.94	0.92	0.87	0.77	0.74	0.83	0.90	0.94	0.69	0.23
Japan	8306-TO	0.48	0.96	0.93	0.85	0.86	0.75	0.64	0.76	0.86	0.94	0.59	0.39
	8411-TO	0.57	0.96	0.93	0.89	0.86	0.60	0.64	0.64	0.84	0.94	0.69	0.38
United	AIG-N	0.61	0.96	0.91	0.87	0.86	0.77	0.55	0.65	0.82	0.88	0.58	0.39
States	BAC-N	0.60	0.95	0.95	0.90	0.87	0.76	0.63	0.69	0.86	0.90	0.67	0.37
	C-N	0.64	0.95	0.92	0.89	0.86	0.73	0.70	0.81	0.89	0.93	0.74	0.35
	MS-N	0.62	0.94	0.94	0.90	0.87	0.82	0.73	0.78	0.89	0.94	0.72	0.37
	PRU-N	0.65	0.97	0.96	0.94	0.87	0.81	0.66	0.75	0.86	0.94	0.78	0.37
Rest	AGN-AE	0.60	0.96	0.96	0.95	0.90	0.87	0.74	0.82	0.90	0.95	0.72	0.34
	NDA’SEK-SK	0.74	0.97	0.96	0.94	0.89	0.84	0.74	0.82	0.88	0.94	0.74	0.27

Table 5.15: **Variable Correlations**

Table 5.15 reports the correlation tables for the variables used in the panel regressions in Section 5.6. Variable symbols are listed below: A: network_stress; B: sys_spillovers; C: size; D: lev; E: closeness; $F1$: in_connections; $F2$: out_connections; $F3$: in_out_connections; $F4$: in_from_other; $F5$: out_to_other; $F6$: in_out_other.

	A	B	C	D	E	$F1$	$F2$	$F3$	$F4$	$F5$	$F6$
A	1	0.362	0.043	0.207	0.604	0.555	0.765	0.736	0.441	0.608	0.617
B	0.362	1	0.157	0.121	0.006	0.020	-0.030	-0.010	0.042	0.003	0.019
C	0.043	0.157	1	-0.114	0.022	0.071	0.014	0.035	0.093	0.044	0.063
D	0.207	0.121	-0.114	1	0.112	0.179	0.187	0.195	-0.034	-0.085	-0.043
E	0.604	0.006	0.022	0.112	1	0.349	0.462	0.448	0.280	0.370	0.378
$F1$	0.555	0.020	0.071	0.179	0.349	1	0.692	0.872	0.864	0.525	0.744
$F2$	0.765	-0.030	0.014	0.187	0.462	0.692	1	0.947	0.542	0.785	0.784
$F3$	0.736	-0.010	0.035	0.195	0.448	0.872	0.947	1	0.718	0.734	0.838
$F4$	0.441	0.042	0.093	-0.034	0.280	0.864	0.542	0.718	1	0.690	0.877
$F5$	0.608	0.003	0.044	-0.085	0.370	0.525	0.785	0.734	0.690	1	0.939
$F6$	0.617	0.019	0.063	-0.043	0.378	0.744	0.784	0.838	0.877	0.939	1

Table 5.16: **Panel Regression Results on Network Defaults - Full Sample**

Table 5.16 reports the panel regression results for network defaults as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method for the models and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses.

	Dependent variable: network_default						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
spillovers	-1.620^{***}	-1.602^{***}	-1.072^{***}	-1.554^{***}	-1.604^{***}	-1.333^{***}	-1.551^{***}
	(0.185)	(0.186)	(0.162)	(0.183)	(0.186)	(0.168)	(0.183)
spillovers2	-0.208^{***}	-0.204^{***}	-0.104^{***}	-0.194^{***}	-0.204^{***}	-0.152^{***}	-0.193^{***}
	(0.032)	(0.032)	(0.028)	(0.032)	(0.032)	(0.029)	(0.032)
spillovers_non_crisis	0.260^{***}	0.271^{***}	0.607^{***}	0.302^{***}	0.269^{***}	0.483^{***}	0.307^{***}
	(0.059)	(0.059)	(0.045)	(0.057)	(0.059)	(0.047)	(0.056)
size	0.060^{***}	0.060^{***}	0.036^{***}	0.058^{***}	0.060^{***}	0.048^{***}	0.058^{***}
	(0.014)	(0.014)	(0.009)	(0.013)	(0.014)	(0.011)	(0.013)
lev	-0.0001	-0.00002	-0.017^{*}	-0.003	0.0001	-0.010	-0.002
	(0.017)	(0.017)	(0.010)	(0.017)	(0.017)	(0.013)	(0.017)
closeness	16.360^{***}	16.360^{***}	-0.297	15.650^{***}	16.360^{***}	7.852^{***}	15.670^{***}
	(1.459)	(1.452)	(0.296)	(1.514)	(1.457)	(1.173)	(1.507)
in_connections		-0.003					
		(0.005)					
out_connections			1.582^{***}				
			(0.021)				
in_out_connections				0.122^{***}			
				(0.022)			
in_from_other					-0.005		
					(0.005)		
out_to_other						0.782^{***}	
						(0.041)	
in_out_other							0.112^{***}
							(0.019)
Observations	70,914	70,914	70,914	70,914	70,914	70,914	70,914
R^2	0.181	0.181	0.308	0.184	0.181	0.247	0.184
Adjusted R^2	0.177	0.177	0.302	0.181	0.177	0.243	0.181

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5.17: **Panel Regression Results on Network Defaults - Subprime and Global Financial Crises**
Table 5.17 reports the panel regression results for network defaults as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses. The sub-sample period is from September 2007 to July 2009.

	Dependent variable: network_default						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
spillovers	-0.471^{**}	-0.470^{**}	-0.229	-0.463^{**}	-0.471^{**}	-0.400^{**}	-0.464^{**}
	(0.198)	(0.199)	(0.171)	(0.196)	(0.198)	(0.176)	(0.195)
spillovers2	-0.091^{***}	-0.091^{***}	-0.056^{*}	-0.090^{***}	-0.091^{***}	-0.083^{***}	-0.090^{***}
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.031)	(0.034)
size	-0.001	-0.001	0.012	0.004	-0.001	0.005	0.003
	(0.028)	(0.028)	(0.018)	(0.026)	(0.028)	(0.016)	(0.026)
lev	-0.022	-0.022	0.013	-0.019	-0.022	-0.006	-0.019
	(0.031)	(0.031)	(0.019)	(0.030)	(0.031)	(0.017)	(0.030)
closeness	9.039^{***}	9.028^{***}	-3.035^{***}	8.321^{***}	9.035^{***}	2.602^{***}	8.232^{***}
	(1.674)	(1.674)	(1.092)	(1.668)	(1.674)	(0.789)	(1.645)
in_connections		-0.005					
		(0.005)					
out_connections			1.218^{***}				
			(0.059)				
in_out_connections				0.131^{***}			
				(0.023)			
in_from_other					-0.005		
					(0.005)		
out_to_other						0.617^{***}	
						(0.026)	
in_out_other							0.137^{***}
							(0.019)
Observations	16,056	16,056	16,056	16,056	16,056	16,056	16,056
R^2	0.137	0.137	0.345	0.147	0.137	0.264	0.150
Adjusted R^2	0.125	0.126	0.316	0.134	0.126	0.242	0.137
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 5.18: **Panel Regression Results on Network Defaults - Eurozone Sovereign Crisis**

Table 5.18 reports the panel regression results for network defaults as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses. The sub-sample period is from May 2010 to May 2012.

	Dependent variable: `network_default`						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`spillovers`	0.505**	0.502**	0.573***	0.519**	0.501**	0.684***	0.539**
	(0.214)	(0.214)	(0.197)	(0.213)	(0.214)	(0.196)	(0.212)
`spillovers2`	0.116***	0.115***	0.137***	0.119***	0.115***	0.153***	0.123***
	(0.036)	(0.036)	(0.033)	(0.036)	(0.036)	(0.033)	(0.036)
`size`	0.022	0.022	0.018	0.021	0.022	0.013	0.020
	(0.017)	(0.017)	(0.015)	(0.017)	(0.017)	(0.016)	(0.017)
`lev`	−0.012	−0.012	−0.011	−0.014	−0.011	−0.015	−0.015
	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)	(0.015)	(0.016)
`closeness`	6.976***	6.956***	0.782*	6.692***	6.954***	3.036***	6.665***
	(1.313)	(1.309)	(0.404)	(1.314)	(1.311)	(0.822)	(1.304)
`in_connections`		−0.004					
		(0.005)					
`out_connections`			0.834***				
			(0.024)				
`in_out_connections`				0.077***			
				(0.018)			
`in_from_other`					−0.005		
					(0.004)		
`out_to_other`						0.499***	
						(0.027)	
`in_out_other`							0.076***
							(0.015)
Observations	17,394	17,394	17,394	17,394	17,394	17,394	17,394
R^2	0.127	0.127	0.281	0.131	0.127	0.240	0.133
Adjusted R^2	0.117	0.117	0.259	0.121	0.117	0.221	0.123
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 5.19: **Panel Regression Results on Network Defaults - Forward Measures**

Table 5.19 reports the panel regression results for network defaults (forward one quarter/year leads) as the dependent variable. Variables are in log forms, so that fitted coefficients represent elasticities. The models use twoway fixed effect method and Newey-West heteroskedasticity-autocorrelation-consistent standard error estimates are reported in parentheses.

	Dependent variable: `network_default`								
	full sample			subset 1			subset 2		
	present	1 quarter	1 year	present	1 quarter	1 year	present	1 quarter	1 year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
`spillovers`	-2.343^{***}	-2.188^{***}	-1.113^{***}	-0.228	0.131	-0.314^{**}	0.561^{***}	2.225^{***}	-0.657^{**}
	(0.156)	(0.143)	(0.165)	(0.171)	(0.094)	(0.126)	(0.196)	(0.205)	(0.258)
`spillovers2`	-0.361^{***}	-0.332^{***}	-0.149^{***}	-0.056^{*}	0.016	-0.046^{**}	0.135^{***}	0.360^{***}	-0.100^{**}
	(0.026)	(0.024)	(0.027)	(0.030)	(0.017)	(0.019)	(0.033)	(0.034)	(0.043)
`size`	0.035^{***}	0.041^{***}	0.019^{*}	0.012	0.046^{***}	0.006	0.019	0.006	-0.040^{**}
	(0.009)	(0.010)	(0.011)	(0.018)	(0.014)	(0.014)	(0.015)	(0.016)	(0.019)
`lev`	-0.014	-0.019^{*}	-0.001	0.013	0.006	0.0004	-0.009	-0.016	-0.038^{**}
	(0.010)	(0.011)	(0.012)	(0.019)	(0.014)	(0.013)	(0.014)	(0.015)	(0.018)
`closeness`	-0.576^{**}	0.019	0.045	-3.066^{***}	-0.576^{***}	0.680	0.645	0.096	0.548^{*}
	(0.286)	(0.317)	(0.042)	(1.091)	(0.211)	(0.429)	(0.400)	(0.252)	(0.331)
`in_connections`	-0.037^{***}	-0.025^{***}	-0.005	-0.010^{**}	-0.009^{*}	0.011^{**}	-0.018^{***}	-0.014^{***}	-0.006
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
`out_connections`	1.584^{***}	0.997^{***}	-0.068^{***}	1.219^{***}	0.609^{***}	-0.276^{***}	0.841^{***}	0.584^{***}	-0.181^{***}
	(0.020)	(0.021)	(0.016)	(0.059)	(0.019)	(0.025)	(0.023)	(0.020)	(0.024)
Observations	70,914	70,914	70,914	16,056	16,056	16,056	17,394	17,394	17,394
R^2	0.307	0.131	0.002	0.346	0.110	0.023	0.283	0.131	0.010
Adjusted R^2	0.293	0.114	-0.018	0.286	0.028	-0.068	0.222	0.057	-0.074
Note:							*p<0.1; **p<0.05; ***p<0.01		

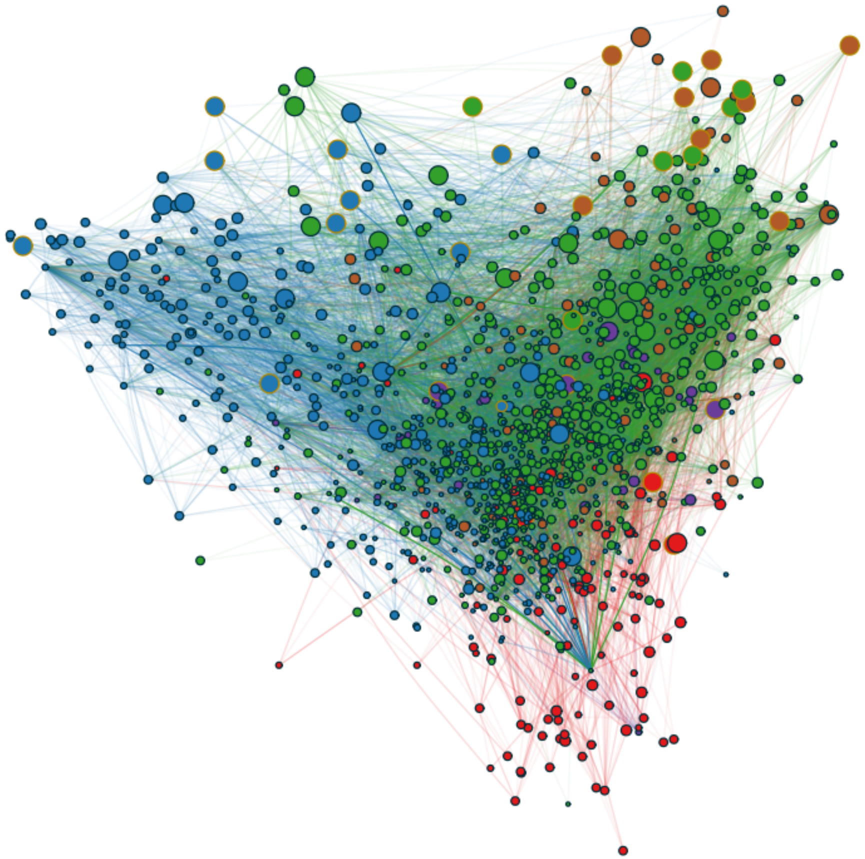


Figure 5.13: Tail-Dependence Network Structure: August, 2007

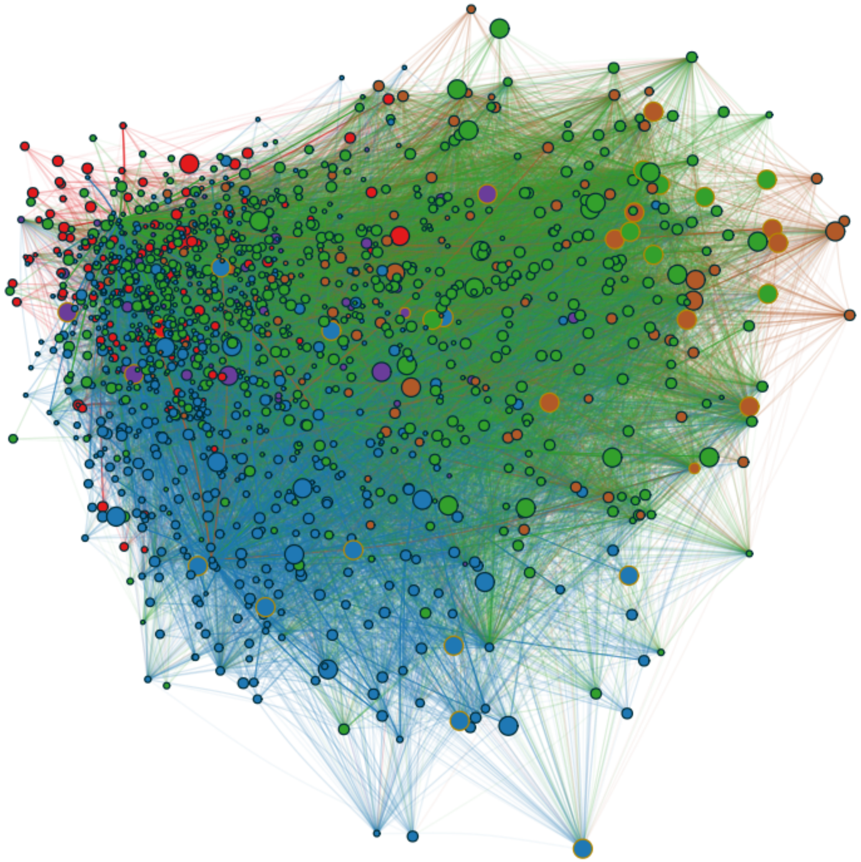


Figure 5.14: Tail-Dependence Network Structure: September, 2008

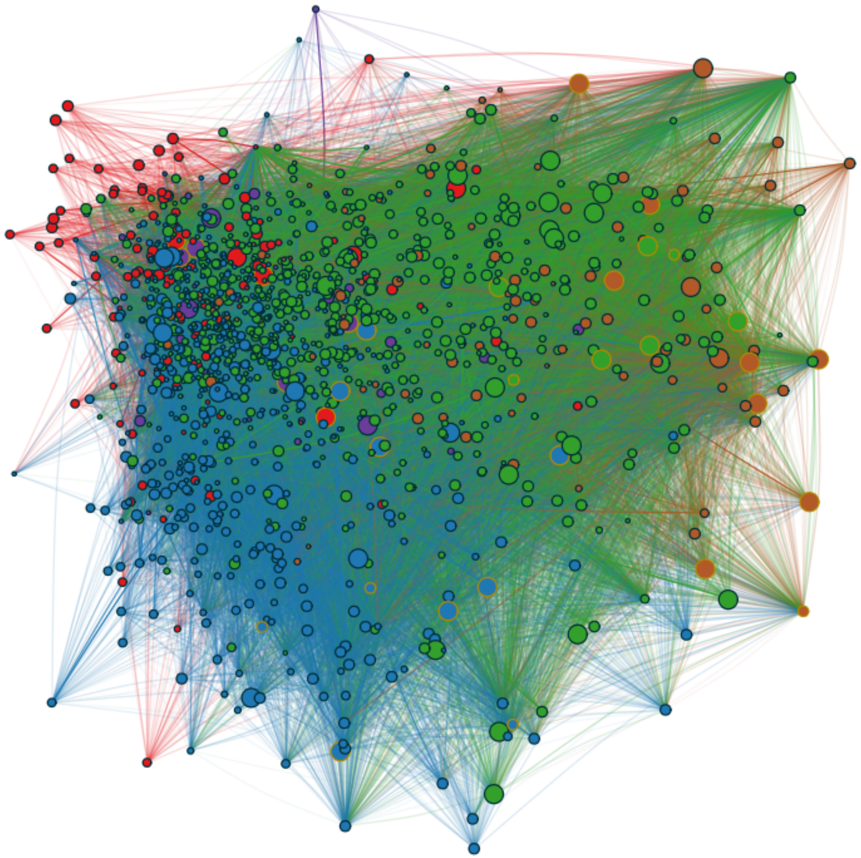


Figure 5.15: Tail-Dependence Network Structure: April, 2009

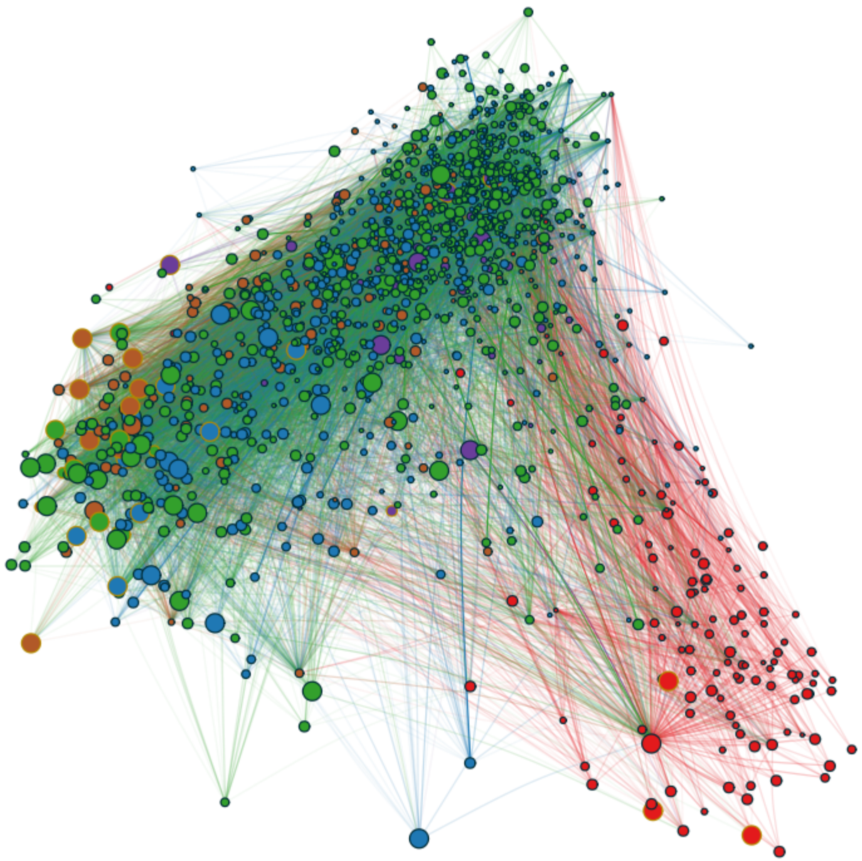


Figure 5.16: Tail-Dependence Network Structure: May, 2010

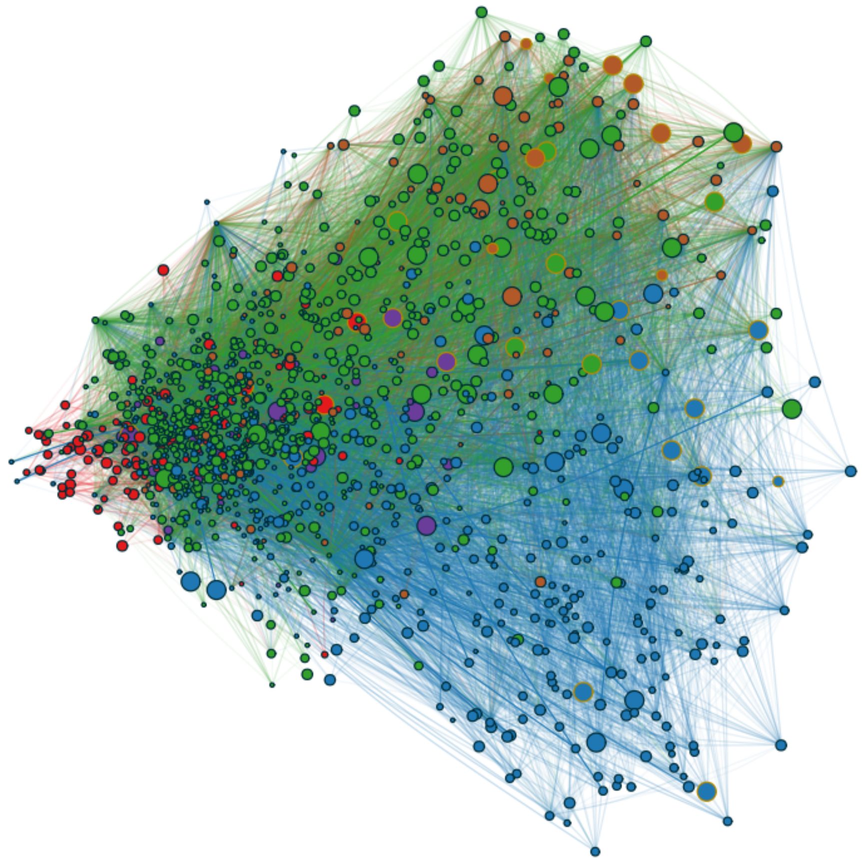


Figure 5.17: Tail-Dependence Network Structure: November, 2011

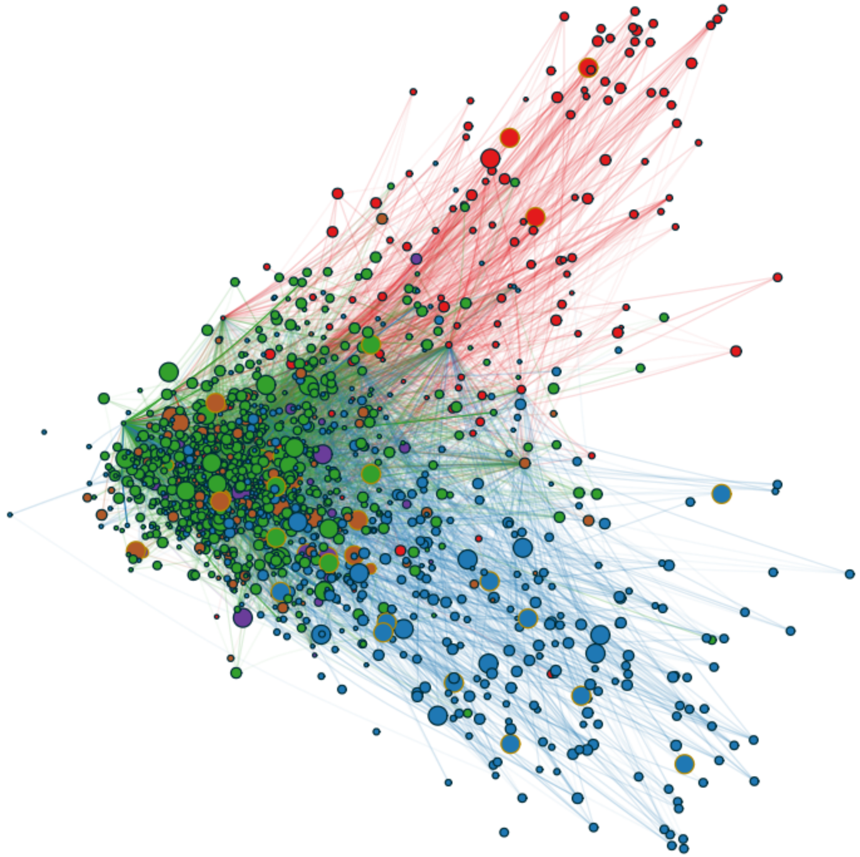


Figure 5.18: Tail-Dependence Network Structure: July, 2013

Chapter 6

Concluding Remarks

6.1 Main Findings and Policy Implications

Primary to our interest, we investigate the risk spillovers from different sources of systemic risk and assess the impact of these risk spillovers to the stability of the financial system. In our research we carry out several studies with advanced empirical frameworks to address our research questions and objectives.

In Chapter 3, we study the risk spillover effects from sovereign credit risk to financial institutions, using sovereign CDS spreads and financial CDS spreads as indicators of credit risk in the two markets. We use the $\Delta CoVaR$ spillovers from a sovereign country to the systemically important financial institutions as the sovereign country's systemic risk contributions. The $\Delta CoVaR$ risk measure is estimated from quantile regression models, where we also examine the structural stability of the risk estimates. In terms of the systemic risk contributions from sovereign credit risk, we find there are several waves of drastic increase in risk spillovers from the distress of sovereign countries, each related to the events of declines in the market confidence regarding the fiscal health in sovereign countries, which is transferred to the market concern about the solvency of financial institutions from their exposure to sovereign credit risk. Our investigation regarding the factors which influence the spillover effects from sovereign countries to financial institutions also confirms that the variables representing the fiscal sustainability and government interventions to the financial markets contribute to the increase in risk spillovers in various degrees, which is inline with other theoretical/empirical findings regarding the sovereign risk spillovers (Drechsler et al., 2011; De Bruyckere et al., 2013).

In order to have a more comprehensive view regarding the impact of sovereign risk spillovers, in Chapter 4, we extend the scope of analysis to sovereign bond markets, sovereign CDS markets, and national banking sector. The $GVAR$ model allows us to examine the impact of sovereign risk shocks from increase in debt burden and the slowdown of economic growth to the markets by methods of impulse response analysis and forecast error variance decompositions. We find strong contributions from the influence of other countries and other markets to the sovereign risk levels as well as financial market returns. In addition, our results support the findings in Chapter 3 and we show that sovereign risk shocks from Portugal and Italy in the distressed country groups and Germany in the core country groups impose greater impact to the overall level sovereign risk in the European Union as well as the national banking sectors.

In Chapter 5, we focus on the risk spillovers among financial institutions and investigate the implications of financial interconnectedness on the impact of systemic risk spillovers. We study the network interconnectedness from the pairwise tail-dependence of financial market returns from the network extensions of the $\Delta CoVaR$ approach. Our analysis on the tail-dependence network encompasses a greater range of global financial institutions than previous studies (Hautsch et al., 2012; Billio, Getmansky, Lo and Pelizzon, 2012; Betz et al., 2015) which allows us to have a broader view on the impact of financial interconnectedness and market distress on the stability of the financial system. In order to analyse the topological characteristics of network interconnectedness, we construct several centrality measures and examine the evolution of the interconnectedness characteristics over the recent crisis episodes. In addition, we examine the propagation of risk spillovers via the dependence structure of market returns to examine the resilience of the financial system from interconnectedness risk and crisis distress. The tail-dependence of financial institutions exhibit a clustering behaviour within their economic zones, which is swiftly blurred by the strong market distress of financial crises. Our study shows that market distress greatly contributes to the drastic increase in tail-dependence which in turn impose great interconnectedness risk to the financial stability.

The findings in our research lead to several policy implications. Firstly, the spillover impact of systemic risk from various sources warrants the further enhancement in the joint efforts of national and supranational authorities in providing financial stability at a greater level, and the establishment of a unified financial resilience framework. We provide empirical evidence regarding the strong risk spillovers either from sovereign credit risk or financial credit risk, as the distress of market participants quickly lead to the transmission of risk to other entities in the financial system. Such phenomenon leads to the further collapse in market confidence and risk sentiment which in turn leads to the sudden drying up of asset liquidity and funding liquidity in the market. In the face of a systemic event that endangers the widely interlinked financial system, individual sovereign country's efforts in stabilising the national financial sector would likely be ineffective given the strong external influence and risk spillovers, and might exacerbate market distress when the capability and resolve of the national authority are put in question. Our results also show that the market sentiment of systemic risk decline substantially after the unifying efforts of market stabilisation schemes from supranational authorities. Therefore, from the perspective of policy-makers, the monitoring and the assessment of system risk need to take into account the globalised interactions of systemic risk spillovers and its impact, and the policy-making regarding financial stability and resilience should also be undertaken in this context. In addition, evidence from the recent crises shows that the establishment of a well-prepared financial resilience facility with clear mandates is most effective way in curbing market contagion and mitigating the impact of systemic risk.

Secondly, greater transparency in market exposures and better availability in measurement data are needed for the monitoring of systemic risk. As discussed in our studies, market participants have no knowledge regarding the market exposures other than their direct counterparties, and regulators also rely on the periodic financial reports and market reports to monitor the stability of the financial system. Regulators and market participants both rely on either direct institutional reports or their own risk measurement models for risk assessment, and the evidence from the recent episodes of financial crises put the effectiveness of the current reporting standards of risk exposures in doubt. While systemic risk measurements based on market series such as interbank interest rates, credit and liquidity spreads allows researchers and regulators to gain the holistic views of the overall market situation, and we expect new generations of market-based risk measures with greater accuracy, the existence of risk spillover effects mean that they are not the perfect substitutes of institutional financial reports and market surveys, and should help policy-makers in laying out foundations of the next generation of financial reporting standards. With the greater integration of markets, new unifying standards in financial reports and market reports with higher frequency and more detailed risk categories that can better reflect the timely risk status in the financial system will be welcomed by both regulators and market participants for a more stable and more resilient financial system.

Thirdly, evidence from our research calls for a more robust market structure with greater heterogeneity in the business models in financial institutions. Homogeneity in business models in market participants leads to them being particularly susceptible to shocks from individual origins of risk, and provide the opportunity to upgrade idiosyncratic shocks to systematic shocks and further to systemic events and financial instability. In other words, "homogeneity breeds fragility" (Haldane and May, 2011). The results from our research show that for national financial sectors as well as individual financial institutions that are less dependent from external sources, especially from a single dominant external influence are less susceptible to spillover impact and recover sooner from the devastations of market collapse. Therefore, from the perspective of mechanism designs, regulators and policy-makers should seek to promote a robust market structure where the impact of risk spillovers could ideally be self-contained within a modular design of market mechanism, in addition, they need to provide incentives for market participants to pursue more heterogenous business models and limit the presence of all-encompassing financial institutions which would be "too-interconnected-to-fail".

6.2 Limitations and Future Research

Our research seeks to provide a deeper understanding of systemic risk spillovers from various perspective, however there are limitations in our studies and further research opportunities based on our studies as well as the relevant studies from the literature strands. Regarding the study in Chapter 3, our empirical evidence is limited by the availability of the measures of the involvement of sovereign countries in terms of fiscal and monetary support to the financial institutions. The data regarding state interventions is collected from official source, which is aggregated to country level and is limited within the European Union member states. An alternative and more robust approach would be to collect the state intervention information from the perspective of individual financial institutions as the bailout or the financial support package they receive. This would involve collecting valid information regarding financial support from financial news and institutional financial report. The most challenging tasks in this approach is collecting an unbiased data population, considering privacy issues and the case of missing information from small financial institutions. To our knowledge, although there are efforts (Gerhardt and Vennet, 2016; Cabrera, Dwyer and Samartín-Saénz, 2016), the absence of unified official data makes the efforts of these studies difficult to validate. Therefore in order to justify for state interventions in the context of supporting financial institutions through crisis episodes, a unified collection of state intervention data in greater details should be provided by national/supranational authorities.

In terms of the choice of measurement models, while our method in measuring the systemic risk contributions of sovereign distress is based on prominent methodology framework that is widely adapted in various studies, one of the limitations in our method is that it is a reduced form empirical measure of systemic risk spillovers. A structural form method based on reasonable and extensible economic models would be of interest from the point of view of policy-makers. However, as discussed from the systemic risk surveys (Bisias et al., 2011; Benoit et al., 2016), reduced form measures or the empirical elements from prominent structural models are more than often favoured by applications in measuring systemic risk due to their succinct nature. While the accuracy in measuring credit risk, liquidity risk, or systemic risk improves substantially from the development in the literature, comparing reduced form market-based measures with studies on the balance sheet characteristics of financial institutions, they contribute not as much to the specific policy decisions regarding how the markets and market participants should be regulated. Therefore it is also in our research interest to assess the actual effectiveness of relevant regulation policies from the empirical evidence of financial markets with the help of structural economic models.

Regarding the study in Chapter 4, our modelling of sovereign risk spillovers is limited by the scope of the *VAR* system, where we only consider the case of countries in the European Union to accommodate the theoretical justifications of the *GVAR* model. To evaluate the impact of spillover dynamics of sovereign distress in a more globalised setting, where the dominant influence of the financial markets of United States could be considered within the accommodation of the *GVAR* model or other types of high dimensional models of economic system, we will have to construct a greater modelling system where most of the economic sub-systems retain their granular presence in the model. In other words, in order to understand the regional spillover dynamics between the European sovereign countries while also considering the influence of the financial markets of the United States, other economic zones will also need to be included in the model and their effects accounted for. Nevertheless, the globalised interaction of various financial markets within a *VAR* system will be of interest to the regulators and policy-makers with a unified view on the global impact of systemic risk spillovers, which we will leave for future studies.

In addition, as is also noted in other studies regarding high dimensional information system (Dees et al., 2007; Chudik and Pesaran, 2014), given the vast amount of parameters of domestic, regional and global interactions, there is currently no full macroeconomic identification guidance for a high dimensional *GVAR* model, which means that there is no convincing ways to structurally identify the structural shocks to the error components or to justify the variable orderings used in the Cholesky

Decompositions. However this is surely in the research interest of economists given a globalised financial system of capital flows and economic policies. A closed system way to model the impact of one or several financial markets without considering the influence and impact from / to the external and global environment will be less validated and supported by the empirical evidence. We gladly welcome the development in the theoretical and empirical frameworks of more globalised financial market models, and will perhaps contribute to such development in the future course of our research.

Regarding the study in Chapter 5, we have shown there are varying structures of interconnectedness of financial institutions; for example, financial institutions that share certain commonalities (affiliations in the same economy or financial sector, similarities in risk exposures and contributions, etc.) tend to be clustered together. In our study, as well as other economic studies on financial network, the centrality of individual nodes is the primary focus of the topological structure of the network system, which means the measurement of network interconnectedness is from the individual nodes *per se*. However, the clusters of nodes would also be an important source of systemic risk. For example, it will be from the interest of regulators to investigate the potential scenario of distress of a cluster of several financial institutions which are characterised by their deep involvement in a specific niche market. The investigation to the network clusters inevitably involves the identification of a network cluster in a certain form, or in other words, what kind of relationship among nodes qualifies as a "cluster" while others do not, which is a research interest worth addressing. In addition, evaluating the effect of the clustering formation and other topological properties of network systems in the context of financial stability in a suitable theoretical and empirical framework will also be an area of research interest.

While our study focuses on the understanding of the tail-dependence of risk spillovers of financial institutions from empirical evidence, an examination of the possible scenarios of tail-dependence under different simulated parametric settings would also be of interest to regulators. Specifically from the perspective of tail-dependence of the market series, for example, to what extent should the policy-makers promote the heterogeneity in the tail-dependence as revealed by the parameters of network characteristics can provide a better market condition, and how robust can the policies be in the likely event of another market crisis? Extending this issue to a wider range of the financial network formulations, such as contractual links, what kind of interbank market structure should the policy-makers promote in order to let banks and other financial institutions enjoy the benefit of risk diversification through interconnectedness while at the same time limit the impact of initial distress from spreading.

While some of these issues would be formidable to address, they will be crucial to the deeper understanding of systemic risk in the financial markets and the responses from market participants, policy-makers, and individual investors. We will be wholeheartedly excited to witness the development in economic research to promote financial stability and resilience, and we will seek to address some of these issues in the future course of our research.

Table A.1: **Crisis Events**
Table A.1 reports events that signify the various stages in the crises discussed in the study.
Source: collected by authors.

Code	Date	Description
01	09 October 2002	NASDAQ and NYSE crash
02	14 September 2007	Bank run on Northern Rock
03	11 November 2007	S&P mass downgrades of securities backed by subprime mortgages
04	14 March 2008	Bear Stearn collapses
05	15 September 2008	Lehman Brothers bankrupts, start of Global Financial Crisis
06	02 April 2009	G20 stimulus package
07	02 May 2010	Greece bailout, 1st round
08	18 November 2010	Ireland bailout
09	05 May 2011	Portugal bailout
10	21 June 2011	Greece bailout, 2nd round early draft
11	11 November 2011	Italy approves austerity measures and changes government
12	21 Februrary 2012	Greece "technical defaults" with finalised 2nd round bailout package
13	06 May 2012	Market fear resurges due to election impasse in Greece

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