ESSAYS ON SYSTEMIC RISK IN FINANCIAL MARKETS

by

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ABSTRACT

The three main chapters of this thesis jointly seek to empirically model systemic risk in financial markets. Chapters 2 and 3 focus on China's stock market at both sectoral and institutional levels. Chapter 2 adopts two recently developed approaches, Marginal Expected Shortfall and Component Expected Shortfall, to evaluate each sector's contribution to systemic risk[1]. Chapter 3 uses conditional Value-at-Risk characterized by dynamic copulas to identify risk spillovers between financial institutions and the financial system. Certain sectors and institutions are identified as key risk contributors. Their contributions exhibit clear time-varying patterns.

Chapter 4 extends to explore regional financial integration across nine stock markets in East and Southeast Asia[2]. Empirical results based on a vector autoregressive (VAR) network approach show that the seemingly high regional stock market integration is largely driven by common global factors. After filtering these factors from individual markets, the interconnectedness falls substantially. The overestimated interconnectedness is mainly a reflection of stronger global influences on individual markets over time, while their intrinsic interconnectedness attributable to non-global factors shows a descending trend after the global financial crisis and its aftermath. These findings offer practical implications to investors and regulators for risk management and regulatory purposes.

[1] Chapter 2 is based on a published article (Wu, 2019a) in *Finance Research Letters*, 2019, 31, 386-390.
[2] Chapter 4 is based on a published article (Wu, 2019b) in *International Review of Financial Analysis*, doi.org/10.1016/j.irfa.2019.101416.

To Dayong and Hengyu

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INTRODUCTION

Since the global financial crisis, it has been central to a diversity of global and domestic regulatory and supervisory bodies to identify the source of systemic risk and its various patterns of amplification and spillovers, in order to gradually shuffle systemic risk regulation from *ex post* recovery to *ex ante* supervision and regulation. Alongside policy transitions and updates from micro-prudential to macro-prudential frameworks, the profound impacts of the crisis have attracted keen interests among academics. The recent decade has witnessed a surge of studies focusing on modelling systemic risk and tracing its trajectories and patterns of contagion.

With its fuzzy nature and multiple facets, systemic risk is yet to gain a consensus on its definition among policy makers, regulators, market participants and academics. Instead, two main characteristics of systemic risk have been generally recognized. Systemic risk is originated from a systemic event, such as distress of parts of the financial system. This event has the tendency of threatening the well-functioning and stability of the financial system, generating material negative externalities to the rest of the economy and severely impairing social welfare (De Bandt and Hartmann, 2002; FSB, 2009; Billio et al., 2012). Against a usual fallacy, systemic risk and systematic risk are two distinct concepts, with the former arising only in a circumstance when the whole financial system is in distress and the amplification and spillover effects are triggered, whilst the latter indicating merely aggregate and undiversifiable market risk (Korinek, 2011).

This thesis aims to contribute to the voluminous and fast-evolving literature and on-going regulatory updates dedicated to detecting and understanding the multiple facets of systemic risk in financial markets. It starts with a brief review of relevant streams of literature, with several seminal theories and models discussed in Chapter 1. In the following three chapters, several advanced quantitative methods are adopted to approach the research questions of measuring systemic risk contributions and capturing the network structure that may facilitate risk spillover. These empirical studies are conducted at institutional, sectoral and market levels, attempting to identity the riskiest components in the financial markets and the most likely paths that risk can transmit across the system. These research questions are highly relevant to market participants, policy designers and practitioners, in terms of identifying the sources of risks and emerging threats to financial stability, as well as promoting the market discipline.

The second chapter investigates the question of how much each sector contributes to systemic risk in the Chinese stock market. Methodologically, this study is mainly based on two recently developed approaches, namely, Marginal Expected Shortfall (MES) and Component Expected Shortfall (CES). From a sectoral perspective, this study seeks to gauge the marginal risk contributions made by the component parts in the Chinese stock market covering both cross-section and time series dimensions. The rankings of the sectors' risk levels calibrated by the MES and CES approaches show that Financials, Industrials and Energy sectors appear to be the top contributors to systemic risk in this system, although their contributions tend to evolve over time. The empirical results also demonstrate that weights of sectors matter, which should therefore be taken into account when evaluating the systemic importance of a given sector.

The third chapter examines the risk spillovers in the Chinese financial system by adopting a time-varying copula-CoVaR approach. Unlike Chapter 2 focusing on sectoral risk contributions in extreme events, this chapter examines how and to what extent risks arising from extreme losses of the key financial institutions, namely, the systemically important financial institutions (Acharya et al., 2012), may spread across sectors/industries and incur system-wide instability, as well as how their own risk levels tend to change when exposed to system-wide extreme losses. In other words, this study seeks to explore the bi-directional tail dependence between individual financial institutions and the financial system. By quantifying VaR, CoVaR and ΔCoVaR through time-varying copulas, we first identify the systemically important financial institutions (SIFIs) for each industry group in China's Financials sector in a dynamic context. We then find strong evidence of upside and downside risk spillovers between SIFIs and the financial system. The empirical results further reveal asymmetric downside and upside risk spillover effects, indicating asymmetric hedging strategies for investors during market upturns and downturns.

The fourth chapter explores the issue of financial integration among stock markets of ASEAN5 economies, plus China (mainland China and Hong Kong), Japan and South Korea (referred to as ASEAN5+4). Asian stock markets are usually said to be increasingly linked in recent years (Chien et al., 2015), especially in the presence of on-going joint policy efforts geared towards a regionally integrated market. Using both graph theory and a vector autoregressive (VAR)-based method, together with rolling window analysis, we show that the level of interconnectedness among these markets is high but with clear time-varying patterns. We further find that a large share of this seemingly high level of integration is shown to be driven by common global factors. After filtering these factors from each stock market by a simple market model drawn on the international capital asset pricing model, the magnitude of interconnectedness falls substantially. Our results therefore suggest that stock market integration in East and Southeast Asia is not as strong as it looks. The overestimated interconnectedness is mainly a simple reflection of stronger global influences on individual markets, while their interconnectedness attributable to non-global factors shows a descending trend after the crisis. Although governments in this region have been promoting financial market collaboration and integration through wide-ranging reforms and regional cooperation, barriers still remain significant. Stock markets in this region are not completely liberalized. Substantial differences exist among the markets in many economic, legal and institutional aspects. Our findings suggest that achieving a highly integrated regional market, if ever possible, should be a slow, painstaking process requiring aligned political objectives and scrupulous policy designs and executions.

The contributions of this thesis are mainly threefold. First, to the best of our knowledge, sparse studies in the extant literature have tried to explore systemic risk contribution or spillovers in the Chinese financial system using MES, CES or CoVaR-copula approaches, or from a sectoral perspective. By investigating risks lying in the multiple levels of the financial market, we hope to provide new perspectives to future researches as well as informative findings to potential users. Based on the advances of these quantitative models, we manage to cover both cross-sectional and time dimensions to depict not only a static landscape but more importantly the dynamic evolution of systemic risk. The combination of portfolio (Chapters 2, 3 and 4) and network (Chapter 4) theories also lays a sturdy foundation to enable us to account for both the

“Too-big-to-fail” and “Too-interconnected-to-fail” paradigms, which are two core ideas guiding policy designs and practices of many regulatory frameworks. Although focusing on the Chinese datasets to account for the growing importance of the fast internationalized and liberalized Chinese equity market on global financial stability (Glick and Hutchison, 2013; Zhang, 2017; Yao et al., 2018), we hope that the new perspectives shown in these studies can be of future use in broader contexts.

Second, our empirical findings offer practical implications to regulators during the process of diagnosing systemic weaknesses and possible sources of risk spillovers during both bullish and bearish periods, so as to enhance resilience of the whole system and promote financial market governance. For stock market participants, these results remind them that systemic risk of the systemically important components and the market as a whole both matter significantly during the process of effective risk management. The asymmetric upside and downside risk spillover effects within the financial system also imply that savvy investors should accordingly predict the dynamics of systemic risk and effectively adjust their hedging strategies and positions to protect portfolios from risk spillovers.

Third, the empirical evidence on Asian stock market integration suggests that although none of the ASEAN5+4 stock markets appears to be completely segmented, their interconnectedness is quite low after filtering out the influences from the world stock market, as opposed to the general perception that domestic stock markets in Asia are becoming more integrated. As the interconnectedness becomes increasingly overestimated over time, the implication is that the ASEAN5+4 stock markets tend to be more exposed to the global factors. The interconnectedness among these markets attributable to non-global factors shows a descending trend after the crises, implying that while potential diversification benefits for global investors still exist, an integrated regional market, although being a long-standing policy goal, is unlikely to be achieved at least in the short run.

1 Literature review on systemic risk: Theoretical frameworks and empirical models

This chapter briefly reviews a battery of theories and models in the extant literature that seek to model or measure systemic risk. It starts with a discussion on the sources of systemic risk explored in the literature. Then quantitative models for measuring systemic risk are then introduced, with their pros and cons briefly discussed. The macro-prudential regulation framework and the identification of systemically important financial institutions (SIFI) are reviewed in the last section.

1.1 Introduction

Modelling systemic risk and curbing its contagion in financial markets have gained increasing attention in the finance literature and regulatory authorities, especially since the 2008 global financial crisis. Since the GFC, it has been central to global regulatory and supervisory frameworks to identify the source of systemic risk and charter the patterns of risk spillovers. The profound impacts of the crisis have given rise to a booming and fast-evolving field of research with concentration on modelling systemic risk and its contagion.

Systemic risk is yet to reach a consensus on its definition among policy makers, regulators, market participants and academics. Billio et al. (2012) define systemic risk as "any set of circumstances that threatens the stability of or public confidence in the financial system". From an alternative perspective, De Bandt and Hartmann (2002) define it as "a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system", which lays particular emphasis on the concept contagion that failures from one institution, market or system propagate to another. Although a unified definition is yet to be gained, its two fundamental aspects have been identified by, for example, the Financial Stability Board (FSB, 2009) and the European Central Bank (ECB, 2010), including the distress of parts or the entire financial system, and a potential of material negative externalities to the rest of the economy and social welfare.

Systemic risk is different from systematic risk. While the latter is aggregate and undiversifiable market risk, systemic risk only arises when the whole banking sector or financial system is facing financial constraints and the financial amplification effects are triggered, according to Korinek (2011).

Given the source of risk, regulators may impose quantified and targeted regulations such as liquidity ratios, based on reliable measures of the systemic risk embedded in the specific risk source. On the other hand, it can significantly aid policy designers to target the riskiest components in the system, if the marginal risk contributions of the component parts in the system can be properly calibrated for both cross-sectional and time series dimensions. The systemic risk models therefore seek to accurately and timely capture both the sources of and key contributors to systemic risk, which are foundations for identifying risks and emerging threats to financial stability and promoting the market discipline.

Regulations concerning the distress of individual institutions constitute the framework of micro-prudential supervision, which does not address inter-institution connections and exposures that may lead to a system-wide collapse. The macro-prudential tools, by contrast, consider the system as a network connecting financial institutions and try to explore the structural vulnerabilities that may facilitate risk propagation and amplification. Borio (2003) defines and compares the macro- and micro-prudential dimensions of regulatory and supervisory arrangements, and suggests a desirable policy effort made on strengthening macroprudential orientation to safeguard financial stability. The interconnected complex network is considered as a key driving force behind recent financial crises such as the episodes of the Lehman Brothers, AIG and the European sovereign debt crisis (Glasserman and Young, 2015).

The remainder of the chapter is organized as follows. In Section 1.2, we review relevant theoretical frameworks in the literature on the sources of systemic risk. In Section 1.3, we introduce the methodologies used in the empirical application for measuring systemic risk. In Section 1.4, we review the empirical models for contagion and risk spillovers. In Section 1.5, we review the relevant literature on identifying and regulating systemically important financial institutions. Section 1.6 concludes.

1.2 Source of systemic risk

Systemic risk can be regarded as a concept involving both risk stemming from a particular source, and its amplification and contagion due to interactions between agents in a network structure that can eventually pose an outsize threat to financial stability. Concerning the source of systemic risk, Bisias et al. (2012) summarize that the origin of historical systemic events stems from the four "L's" of a financial crisis: liquidity, leverage, losses, and linkages. The diversified definitions and sources of systemic risk imply its fuzzy nature. Meanwhile, the complex and multifaceted financial system embeds a diversity of legal and institutional constraints and market practices, and is susceptible to unpredictable exogenous shocks. It seems impossible to develop a single consensus definition or measure that can fully capture the multiple dimensions of systemic risk in this ever-evolving and adaptive financial system.

Accordingly, there has emerged a large body of literature trying to define systemic risk and detect its source. Also, a diverse range of models and measures are developed to capture the many different aspects of systemic risk and to capture the network structure and interaction effects, especially since the 2008 GFC. Bisias et al. (2012) and Benoit et al. (2017) review the literature on the sources of systemic risk and mainstream measures of systemic risk. Chinazzi and Fagiolo (2015) survey the theoretical network-based models aiming for exploiting the sources of contagion and systemic risk in financial markets. A detailed survey of the literature on systemic financial risk and the main paths of research in this field can also be found in Silva et al. (2017).

As it is almost impossible to have an exhaustive overview of the voluminous literature regarding the sources of systemic risk or models of measuring systemic risk due to its complexity and fast evolution, this part represents our attempt at summarizing what we believe to be the most important sources of systemic risk according to the extant theoretical studies, as well as the most representative and popular methodologies.

1.2.1 Herding and correlate risk exposures

One strand of literature explores the mechanism that many banks in the system endogenously choose to invest in highly correlated assets (herding), and their payoffs from the investments are positively correlated whilst their risk exposures are similar. This high correlation in risk exposures increases the aggregate risk in the system and enhances a risk amplification mechanism, leading to simultaneous default and a system-wide failure. Benoit et al. (2015) discuss the correlated risk exposures of financial insitutions, which arise due to cpaital regulations, shared information, and banks' incentives of herding. They investigate whether banks exhibit commonality in trading and whether correlated risk exposures are enhanced when banks are under stress.

Acharya (2009) analyses possible reasons for the herding effect and argues that the market mechanism of limited liability cannot force banks to internalize the negative externalities created by their risk-taking decisions. One bank's failure reduces aggregate fund supply and investment, leading to a "recessionary spillover" to surviving banks who suffer from shrinking profitability due to increased market-clearing deposit rates. The negative externality is found to exceed the positive externality gained by absorbing deposits from migrated depositors and acquisition of failed banks' assets and business, especially when the failed bank is "large" (implying substantial reduction in aggregate investment), "essential" (making depositor migration impossible) or "unique" (making acquisition impossible).

The optimal choice of banks to survive or fail together leads to the preference of high correlation of asset returns. The herding incentives of banks to maximize the likelihood of being bailed out are also discussed in Acharya and Yorulmazer (2008a). For fear that a collective failure of many banks and asset liquidation could harm the broader economy, governments barely have any better choices but to intervene and bail them out, thus giving banks incentives to take the best advantage of this "too-many-to-fail" bailout guarantee by taking the same risks and failing together. Similar insights are proposed by Farhi and Tirole (2012) who analyse the leverage and maturity mismatch in the banking sector and find that herding is an optimal choice for banks, as bailout measures can be costly for the governments and affect the rest of economy, such as maintaining low interest rates. It is therefore optimal to bail out banks together when they all fail. This herding incentive of banks cannot be mitigated by certain bank-specific regulations such as disclosure policies or capital adequacy requirements, indicating that the design of prudential regulations should address both the bank-specific risk and its correlated risk with other banks in a multiple bank context. Acharya and Yorulmazer (2008a) propose a liquidity provision policy which subsidizes surviving banks in acquiring failed banks' assets to avoid the situation where a sufficient price drop attracts liquidity-endowed outsiders to enter the market, leading to allocation inefficiencies. Banks are therefore more incentivized to differentiate *ex ante* as opposed to herding and expecting *ex post* bailout which increases the *ex ante* likelihood of systemic crises.

1.2.2 Liquidity risk

Financial institutions are vulnerable to funding illiquidity. One form of systemic risk in the literature concerns the collective liquidity risks which arise when financial institutions overinvest on illiquid assets in a correlated manner. Bolton et al. (2011) analyse two liquidity sources to meet banks' short-term liquidity needs: proceeds from asset sales or their own cash reserves. The former is more efficient, as holding cash is costly. Delayed trading of assets as the last resort is more effective under complete and symmetric information. In the presence of asymmetric information, however, assets are immediately liquidated with the anticipation of a shock, which leads to excessive early asset liquidation and excessively high cash holding. Bhattacharya and Gale (1987) document the free-riding incentive that drives banks to excessively invest in illiquid assets and rely heavily on interbank borrowings from banks with liquid assets for liquidity, leading to a maturity mismatch and potentially exposing the whole system to aggregate liquidity shortage. A liquidity shock can therefore propagate across the whole network and hit them all.

The interactions between the funding liquidity of traders and market liquidity are discussed by Brunnermeier and Pedersen (2009). The authors find that this type of interactions can lead to liquidity spirals and help explain sudden liquidity dry-up in the market. Flannery (1996) studies market freezes following an extreme case of illiquidity. Brunnermeier and Oehmke (2013b) propose a model of equilibrium maturity structure for a borrower versus multiple creditors. They show that when a firm seeks to dilute the claims of existing long-term creditors by raising new short-term debts, creditors expect substantial default-relevant interim information and thus opt for shortening the maturity by providing better short-term interesting rates, leading to a "maturity rat race" where all banks rely excessively on short-term debts. More examples of liquidity risk models are proposed by, among others, Kapadia et al. (2012) who construct a quantitative model to analyse the interaction between shocks to fundamentals and funding liquidity risk, which causes contagion to spread across the financial system; Diamond and Rajan (2011) who study liquidity dry-ups from anticipation of fire sales; Brunnermeier et al. (2014) who present a theoretical liquidity measure, the Liquidity Mismatch Index (LMI), to assess liquidity risk from firms and macroprudential perspectives; etc.

Furthermore, financial institutions seeking for short-term finance to meet their liquidity needs can entail the so-called roll-over risk. Allen et al. (2012) model another type of inter-bank network arising from asset swap and show that the failure of funding roll-over is a source of systemic risk, caused by the interaction of debt maturity, information and banks' asset structure. With the use of financial instruments such as credit default swaps, banks are allowed to swap assets to diversify their individual risks, thus forming a network and increasing overlaps in banks' portfolio holdings and asset commonality. In case of short-term finance, investors perceiving bad news of banks' future insolvency choose to stop rolling over the debts. The failure of debt roll-over forces early liquidation of assets and therefore generates systemic risk arising from commonality in asset holding. Debts are more likely to be rolled over in an unclustered network where banks hold different portfolios and defaults are more dispersed, than in a clustered network where all banks hold the same portfolio and default together, as information spillover is greater in the latter case. Unlike the domino effect model (Eisenberg and Noe, 2001), this model focuses on asset commonality as a source of systemic risk under information externalities and short-term finance. Paligorova and Santos (2014) find that banks relying heavily on short-term funding attempt to reduce exposure to rollover risk, thus engaging less in maturity transformation. This leads to a potential synchronization of both banks' and their borrowers' rollover risk, which can be a source of financial instability when troubles occur in short-term funding in the market. The roll-over risk can lead to market freeze (Acharya et al., 2011) and dynamic bank runs (He and Xiong, 2012).

1.2.3 Tail risk

Tail risks have been identified as an important source of systemic risk and have been extensively explored in the extant literature. Perotti et al. (2011) find evidence that higher capital reserves may unintendedly enable banks to take more tail risks without the concern of breaching minimal capital ratio requirements (for example, the Basel III rules), as opposed to the traditional argument that higher capital reduces the incentive of excessive risk-taking due to limited liability (Jensen and Meckling, 1976; Holmstrom and Tirole, 1997). Gennaioli et al. (2013) propose a shadow banking model showing that the shadow banking system can create extreme financial vulnerability to crises when securitization facilitates aggregate risk-taking and tail risks are neglected by investors and intermediaries.

1.2.4 Information feedback loop

Shared information and a feedback loop should be considered in exploring the building-up of systemic risk in the financial system. Risk-based trading strategies and risk sensitive regulations, based on historical data, neglect the feedback effect and the endogenous nature of market risk, and can induce unintended detrimental effects on asset price volatility and market distress. Earlier models have shown that the timing of uncovering pertinent information in the market can be an important determinant of investors' decision making (Hirshleifer et al., 1994). Extending these arguments to financial institutions behaviours, Daníelsson et al. (2004) model that market participants' shifts in believes and reactions can affect the uncertainties and risks of asset returns, thus forming a feedback loop. Morris and Shin (1999) point out that risk management strategies that consider risks as exogenous fail to capture the feedback effects of market participants, and taking similar trading positions by many financial entities leads to concerted selling pressure which amplifies price movements and causes liquidity dry-up.

1.2.5 Regulatory constraints

Regulations on financial institutions can also induce unintended consequences and increase market risk. For example, capital regulations can be one reason of correlated risk exposures of financial institutions. The risk-sensitive capital requirements, introduced by the Basel Accord of 1988, are typically represented as a function of the risk of a firm's assets. Selling low risk assets thus affects far less of the firm's ability to meet the capital requirements than sales of high risk assets, even at fire-sale prices, which accelerates the formation of a systemic crisis. Brunnermeier and Pedersen (2009) argue that when the market is experiencing high volatility, financial institutions face increased regulatory capital requirements, and have to liquidate their positions to meet the requirements. This leads to further market volatility. Benoit et al. (2015) provide empirical evidence that the tightended Value-at-Risk (VaR) constraints after a shock force banks to rebalance their risk exposures in the same direction and at the same time, which exacerbates the shock. Merrill et al. (2013) discuss the situation where financial institutions subject to risk-sensitive capital requirements are forced to engage in fire sales of stressed securities.

1.2.6 Macroeconomic conditions

A reading of the most recent macro-finance literature reveals that systemic risk is closely linked to and affected by macroeconomic conditions. One strand of literature looks at credit cycles, such as the seminal overlapping generation model of Bernanke and Gertler (1989) showing that temporary shocks in net worth caused by financial market imperfections are amplified and persist. Holmstrom and Tirole (1997) present a principal-agent model and show that firms with low net worth have to rely on financial intermediaries to reduce collateral requirements, but are subject to more intensive monitoring. Intermediaries also need satisfy market-determined capital adequacy ratios, which are procyclical. Kiyotaki and Moore (1997) model the dynamic interaction between credit constraints and asset prices that gives rise to a transmission mechanism through which small and temporary shocks to technology or income distribution might be amplified and lead to large and persistent fluctuations in asset prices.

Korinek (2011) finds that banks make *ex ante* financing decisions by taking excessive systemic risk while insufficiently insuring them, and do not internalize their contributions to aggregate price depressing when they engage in fire sales, imposing pecuniary externalities on other banks and triggering amplification effects that hurt the wider economy. Boissay et al. (2016) show that moral hazard and asymmetric information issues in the interbank market composed of heterogeneous banks give rise to sudden market freezes, credit crunches, banking crises and eventually severe recessions, as an outcome of “credit booms gone wrong” rather than big negative exogenous shocks. The macroeconomic implications of financial frictions leading to persistence and amplification are also studied in, for example Brunnermeier and Sannikov (2014), and surveyed by Brunnermeier et al. (2012).

Second, the leverage cycle also plays an important role in building up systemic risk. Adrian and Shin (2010) document that the leverage among market-based finacnial intermediaries is strongly procyclical where mark-to-market accounting is a comon practice, leading to an inherently procyclical financial market and enhaced systemic risk. Adrian and Shin (2014) examine how the leverage cycle of the financial system affects flucations of credit supply and fiancial stability. Acharya and Viswanathan (2011) argue that leverages built up during good times result in more de-leveraging when there is an adverse shock, leading to sudden dry-up of funding liquidity in the market arising from fire sales. Bhattacharya et al. (2011) disucss over-leveraging and moreover the shift of investments from safer to riskier projects, as a result of prevalent optimism among financial institutions during prolonged prospecrity. Both studies find that the increased riskiness in the financial system before the crisis leads to more default after the shock and more servere consequences for financial stability.

Third, bubbles can lead to a collapse and widespread default in the financial system. Brunnermeier and Oehmke (2013a) survey the theoretical literature on bubbles, financial crises and systemic risk. Allen and Gale (2000a) model bubbles in asset prices as a result of risk shifting when lenders are unable to observe the risks in borrowers' investments. Allen and Carletti (2013) present a model of real estate pricing and find that real estate boom and bust cycles are the primary cause of financial crises. Acharya and Naqvi (2012) find that volume-based compensation to bank loan officers gives rise to excessive risk-taking during bank lending. Also, following external macroeconomic shocks, investors switch from direct investment to bank deposits. With a surge of increased liquidity, banks' sensitivity to downside risks reduces and loan standards are relaxed, forming credit booms and asset price bubbles.

1.2.7 Network and contagion

Financial networks have been largely studied in the extant literature. Among the many networks in the financial system, the interbank network has received most attention in academic research. As argued by Allen et al. (2012), when one institution suffers a loss due to not necessarily systemic shocks but its idiosyncratic shocks, its risk may spill over and affect other institutions which are connected to it through three possible channels: the interbank market, the payment system, or asset prices. In the presence of these interconnections, one financial institution's failure can propagate and result in default of others through a domino effect.

The interbank market can be viewed as a counterparty network composed of interbank financial linages (edges) and financial institutions (nodes). This network structure can contribute to the accumulation and propagation of systemic risk. Systemic risk and its contagion in the interbank network have been modelled with a diversity of theoretical focuses, such as bank run (Diamond and Dybvig, 1983), common pool of liquidity (Bhattacharya and Gale, 1987; Allen and Gale, 2000b; Diamond and Rajan, 2005; Brunnermeier and Pedersen, 2009), payment system and depositor coordination failures (Berger et al., 1996; Freixas and Parigi, 1998; Freixas et al., 2000), interbank lending and peer monitoring (Rochet and Tirole, 1996; Holmstrom and Tirole, 1997; Gofman, 2017), maturity mismatch (Zawadowski, 2011), liquidity hoarding (Acharya and Skeie, 2011), bilateral hedging contacts (Zawadowski, 2013), asset prices and regulatory capital constraints (Cifuentes et al., 2005), information about asset quality (Chen, 1999; Acharya and Yorulmazer, 2008b), etc. Allen and Babus (2009) survey the literature on interbank markets and the financial network. Surveys on risk contagion are also found in Allen et al. (2009) and Upper (2011).

Interbank exposure network

The research on interbank-claims and balance sheet contagion is well established. While the interbank network brings several benefits to the system, it can also act as a risk transmission channel. One most direct way that risks and losses can propagate in the system is the balance sheet contagion. Systemic risk contagion is present due to the interwoven network in the financial system formed by financial obligations among financial institutions who are borrowers and lenders at the same time. This network structure has played an important role in propagating financial shocks in the system during crises. One single firm's default can directly lead to balance sheet losses of others, triggering a domino effect. This direct network dependence and domino contagion is modelled in Eisenberg and Noe (2001), and empirically investigated in, for example, Upper and Worms (2004) and Degryse and Nguyen (2007), based on simulation techniques. These empirical evidences, however, find that contagion and crises generated by the direct domino effects rarely occur. They occur only when the initial shocks are very large.

Relative to financial linkages as a result of cross-holdings of debts, correlated risk exposure in portfolios is argued to be a far more important driving factor of systemic risk (Elsinger et al., 2006a). According to Brunnermeier and Oehmke (2013a), a big drawback of the domino effect model is that it analyses the network structure and direct bilateral exposures from a static perspective and views financial institutions as passively being exposed to external shocks, thus ignoring possible interactions and feedbacks that may drive the evolutions in the market network structure and amplify the effects of the initial shock. Another issue omitted in the domino model is the possible risk contagion channel through asset price declines. While the domino model is concerned with the direct losses on interbank loans due to individual firms' failures, it does not address the possibility of risk passing down via other channels, such as decreasing asset prices and tightening financial constraints that spread system-wide contagion which all the firms in the network are prone to. The model of Cifuentes et al. (2005) takes into account asset prices in modelling the domino-type contagion to illustrate both channels for risk contagion, which can reinforce each other and amplify the contagion effects. In a same vine, Elsinger et al. (2006a) combine interbank financial linkages and correlation in banks' exposures to study the source of systemic risk.

Another strand of literature focuses on the interbank market and bank runs. While the seminal bank run model of Diamond and Dybvig (1983) considers an economy with a single bank by viewing it as representing the financial intermediary industry, Allen and Gale (2000b) study banks connected in a network based on cross-holdings of deposits, which enables banks to pool liquidity risk and insure each other through the interbank deposits. While this interconnection can serve as a useful tool to reallocate liquidity across banks, it cannot increase the overall liquidity in the banking system. A small sudden liquidity shock may cause a bank to liquidate some long assets, triggering a bank run and liquidation of the bank if the liquidity amount is large enough. Other banks holding deposits in the defaulting bank suffer from losses and their capability of meeting liquidity demands also decreases, which may lead to more premature liquidation of long assets and bank runs. The authors find that the network structure matters in driving system-wide contagion. In a complete market where all banks are cross-holding deposits with each other, the initial shock can attenuate as it is evenly absorbed by all the other banks. By contrast, in an incomplete market where one bank is only linked to a small number of other banks, contagion is more likely to happen.

Kapadia et al. (2012) argue that the contagion of a funding liquidity shock to one bank can propagate through several channels. The distressed bank may engage in liquidity hoarding by shortening the maturities of interbank loans it issued, or completely cutting off the provision of interbank loans, thus reducing the liquidity in the interbank market and causing funding illiquidity to other banks. It may also be forced to sell assets for liquidity, which depresses market prices and leads to mark-to-market losses and distress of other banks due to margin calls. The confidence contagion among market participants may also result in banks runs. The counterparty credit risk arising from the interbank market contagion can lead to more failures of other banks.

As mentioned before, Bhattacharya and Gale (1987) document that the interbank network can also serve as a liquidity pool, and therefore incentivizes banks to overinvest in illiquid assets while seeking for liquidity from borrowings from banks with liquid assets. As banks' liabilities are usually very liquid and short-term, excessive investment in illiquid assets leads to a maturity mismatch. In equilibrium, when all banks exhibit this free-riding incentive and collectively overinvest in illiquid assets, a network is formed through the interbank market and the aggregate liquidity shortage in the banking system tends to increase substantially, exposing the whole system to a liquidity risk propagating across the whole network and hitting them all.

Zawadowski (2011) models the externalities of the interwoven network of financial intermediaries that expose the system to uncertainty contagion. When a funding shock causes funding uncertainty of a bank, it may not commit itself to rolling over the loans it has made. Instead, it tends to hoard cash to serve short-term repayment purposes, which leads to inefficient liquidation of its real assets. This one bank's funding uncertainty further spreads to other banks due to interbank liabilities via the interwoven network, thus magnifying the negative effects of the shock. Gai et al. (2011) model a network of interbank lending with unsecured claims, and find through simulations that greater complexity and concentration in the network can play an amplifying role on the systemic fragility.

Bipartite bank-asset network

Allen et al. (2012) show that asset commonalities between firms can cause information contagion and thus affect the likelihood of systemic crises. They argue that the possibility of information contagion stemming from banks' short-term finance increases with the degree of overlap of banks' portfolios. They also show that a clustered network where banks have same asset structures entails higher systemic risk.

Elliott et al. (2014) and Cabrales et al. (2017) model a network of firms with financial interdependencies formed by cross-ownership of equity shares or assets, where one firm's failure may result in losses of all firms holding its shares, thus triggering a chain reaction or cascading failures (Elliott et al., 2014). On the other hand, securitization in a form of exchanges of assets among firms may increase system-wide financial instability (Cabrales et al., 2017).

Interbank payment network

Liquidity demand arises as banks are spatially separated and depositors have uncertainties about where to consume. This gives rise to needs for a payment system or an interbank market. An interbank network is thus formed in the presence of consumers' spatial uncertainties of liquidity needs. Banks are allowed to minimize their cost of holding low-return liquid assets relying on the interbank market, and the system is more resilient to withstanding a single bank's insolvency since interbank connections transfer losses to other banks via interbank liabilities. However, inefficient outcomes may arise with the existence of the interbank credit line and payment system. Townsend (1987) first studies how agents' spatial separations, private information, ability of communicating with each other over space and time may affect default possibilities. Berger et al. (1996) discuss the main theoretical issues of systemic risk associated with the payment system. Rochet and Tirole (1996) study the peer monitoring on the interbank market. Freixas and Parigi (1998) set up a model of two banks and study the systemic risk as a result of contagion and efficiency associated with a daily interbank payment system.

Freixas et al. (2000) study liquidity provision by the interbank credit lines and by the central bank. They find that the interbank relations expose the system to depositors' coordination failures even if all banks in the system are solvent. Coordination failures among depositors can induce excessive liquidation of productive investment. Insolvent banks may continue inefficient operating as liquidation incentive reduces due to implicit subsidies offered by the payment networks, while solvent banks prone to contagion effects stemming from insolvent banks may have to be inefficiently liquidated. Financial authorities' interventions play an important coordinating role in mitigating these inefficiencies.

A more recent study of Afonso and Shin (2011) investigates the gross settlement payment systems where banks' outgoing payments are heavily financed by incoming funds. The smooth function of such a system thus requires a high degree of coordination and synchronization, giving rise to a multiplier effect that individual banks' cautious behaviour can be magnified to significantly disrupt the normal functioning of the whole payment system. Soramäki and Cook (2013) develop a systemic risk measure called SinkRank based on absorbing Markov chains, to predict the level of system-wide disruption caused by a bank's failure in a payment system, and the effects on other banks in the system.

1.2.8 Amplification

In the presence of amplification mechanism in the financial system, risks can be amplified and small shocks to the systemic components in the system can end up affecting many institutions and eventually generate massive losses. The mechanism of risk amplification leading to perpetuating crises can be twofold: the frictions on the borrower's side, or on the lender's side.

The former case assumes that capital of the lender is sufficient, while the borrower's financial constraints lead to risk amplification and a persistent crisis period, as in the seminal model of Kiyotaki and Moore (1997). In the latter case, the lenders have limited capital and their lending capabilities are restricted when facing worsened financial situation themselves, leading to tightening liquidity in the market and shock amplification. Identifying the mechanism is highly relevant to regulatory intervention in terms of who to recapitalize or subsidize during the crisis.

Holmstrom and Tirole (1997) propose an incentive model which combines the capital constraints of both borrowers and lenders and find that the poorly capitalized firms are most seriously affected by any kind of capital tightening. Furthermore, compared to the situation where multiple investors monitor a same borrower with duplicated monitoring efforts, it can be much more efficient that lenders lend to the borrower through a delegated financial intermediary, as the monitoring is conducted only through the intermediary. This important monitoring role of financial intermediaries is proposed in as early as Diamond (1984). The financial intermediaries, however, need to be sufficiently incentivized to do so. Only when the financial intermediaries have large enough stake in the creditor's project they finance, will they impose sufficiently diligent overseeing on the management of the creditor. Moral hazard may arise when the stake decreases, and the intermediary may thus stop monitoring as a result of lowered incentives, leaving the market to a situation with direct lending but no monitoring, thus loading up risk.

Alternatively, financial intermediaries may engage in liquidity hoarding, based on either precautionary motives when they have the concern of funding insufficiency for further investments and anticipation of interim shocks, or speculative motives of exploiting future fire-sale purchase opportunities (Gale and Yorulmazer, 2013). The inefficient liquidity hoarding in the banking sector leading to an inter-bank market freeze is analysed, in for example, Acharya and Skeie (2011).

1.3 Measuring systemic risk

Based on the manifold nature of systemic risk, models dedicated to measuring systemic risk are highly heterogeneous with focuses on capturing different facets of systemic risk. They can be broadly divided into two main groups: theoretical and structural frameworks of systemic risk and financial intermediation focusing on microeconomic or macroeconomic aspects, and quantitative methods emphasizing empirical applications. Bisias et al. (2012) survey 31 quantitative measures of systemic risk in the economics and finance literature, based on the notion that the origin of historical systemic events stems from the four “L’s” of financial crisis: liquidity, leverage, losses, and linkages.

The quantitative models can be further divided into four categories classified by their statistical methodologies according to Härdle et al. (2016): the quantile regression models such as the linear bivariate models proposed by Adrian and Brunnermeier (2016), Acharya et al. (2012) and Brownlees and Engle (2017), the high dimensional linear models proposed by Hautsch et al. (2014) and Betz et al. (2016), and the partial quantile regression models by Giglio et al. (2016) and Chao et al. (2015); principal component analysis such as Bisias et al. (2012), Eichengreen et al. (2012) and Rodríguez-Moreno and Peña (2013); default probability models such as Lehar (2005), Huang et al. (2009) and Giesecke and Kim (2011); graph theory and network topology analysis, such as Boss et al. (2004) and Diebold and Yilmaz (2014).

Alternatively, considering the frequency of data employed, Rodríguez-Moreno and Peña (2013) categorize systemic risk measures into two groups: high frequency measures derived from market data, and low frequency measures extracted form balance sheet data or macroeconomic indicators. Considering data sources, Benoit et al. (2017) and several others (Chen et al., 2014b; Banulescu and Dumitrescu, 2015) divide the systemic risk quantifying models in to two main categories: market-based approaches and balance sheet-based approaches. The former relies on publicly available data such as stock prices to investigate systemic risk and assess individual firms' risk contribution, while the latter employs balance sheet data or publicly unavailable data to analyse the risk of individual components in the system. The logic behind these two taxonomies are intrinsically similar.

The market approaches generally rely on market data, such as market returns, total asset returns, option prices or CDS spreads. The basic idea is to reveal the financial interdependencies without knowing the exact cross-positions between financial institutions, which in many cases are firm-level private information unavailable to the public (Banulescu and Dumitrescu, 2015). Compared to the balance-sheet approaches with lags in data, the market approaches based on high frequency data have advances in several regards. Data are easily accessible with higher frequency, which enables real-time monitoring and timely capturing of market dynamics and sentiments of information users. The information conveyed by the market asset prices is forward-looking, which greatly facilitates the detecting of early warnings and *ex ante* regulating (Huang et al., 2009; Kritzman et al., 2011; Patro et al., 2013). However, a common drawback of these market data-based measures is claimed to be a general lack of theoretical foundation or power to clearly identify the source of risk (Benoit et al., 2017). Moreover, due to the sources of data, these methods are only suitable for research on listed firms and are subject to modelling risk (Danielsson et al., 2016).

Low frequency measures, by contrast, can provide valuable backward-looking information, if accurately measured, and therefore have the advantage of tracking the evolution of potential imbalances and the building-up of fragility in the financial system or individual firms (Rodríguez-Moreno and Peña, 2013). Also, despite that market data reflect rich information of public information about risk exposure, some private information may often be omitted due to absence of data, which should also be of paramount importance for supervisory purposes (Elsinger et al., 2006b). Balance sheet ratios are largely adopted as systemic risk indicators by regulatory bodies, such as the Financial Soundness Indicators by the International Monetary Fund (IMF, 2006), as well as in academic studies (Borio and Drehmann, 2009; Schwaab et al., 2011, among others).

1.3.1 Low frequency data approaches

Balance sheet approach

The balance sheet approach is closely related to the interbank network composed of financial institutions (nodes) and counterparty financial linkages (edges) formed by the interbank payment system (Freixas and Parigi, 1998), bipartite bank assets (Allen et al., 2012), or interbank exposure (Upper and Worms, 2004; Nier et al., 2007). While Allen and Gale (2000b) argue that the interconnectedness in the financial system increases the system's resilience to the insolvency of any individual financial institution, Acemoglu et al. (2015), among others, show that excessive interconnection leads to increased frangibility of the financial system.

The correlated risk exposures and interbank financial linkages essentially regard the financial system as a counterparty network. One stream of approaches based on this logic seeks to detect the underlying degree of interconnections in the system without directly observing them but through simulation approaches. With available accounting data, the common steps include first constructing a matrix of inter-institution exposures, and then simulating to explore the effects of individual default and further track the domino effect triggered by the event. Nier et al. (2007) examine varying network formation parameters including the level of capitalization, degrees of interconnection, interbank exposures and concentration of the system, to estimate the likelihood of a knock-on effect, and conduct a simulation of inter-bank contagion. Some more recent applications and discussions are found in, for example, Blei and Ergashev (2014) who measure systemic risk driven by asset commonality using a cluster analysis approach based on balance sheet data; Greenwood et al. (2015) studying the contagion effect due to fire sales using European bank balance sheet data to computer bank exposures to system-wide deleveraging; Aldasoro and Angeloni (2015) deriving six indicators based on a matrix of lending and borrowing positions in the interbank market to capture different aspects of systemic importance that contribute to balance sheet contagion, etc. Upper (2011) and Summer (2013) provide detailed reviews of the simulation models of interbank exposures and default cascades/contagion in the network of financial linkages through balance-sheet mechanisms.

Within the framework of domino contagion proposed by Eisenberg and Noe (2001), Upper and Worms (2004) use bank balance sheet data to estimate a matrix of bilateral credit relationships in the German interbank market. Degryse and Nguyen (2007) collect data from a confidential database of bank balance sheets to study aggregate interbank exposures in the Belgian banking system. Elsinger et al. (2006a) combine interbank financial linkages and correlation in banks' exposures to study the source of systemic risk, using both accounting data and stock market data. Also built on the Eisenberg-Noe framework, Glasserman and Young (2015) consider the dynamic process of the link formation in the network, with an application to the European banking system using supervision data from the 2011 stress test by the European Banking Authority. Kanno (2015) considers a multi-period setting and analyses the bilateral exposure matrix using aggregate balance sheet data and the interconnectedness in the interbank market using network centrality measures, which confirms the central role played by the designated G-SIBs, namely, the global systemically important banks, in the global interbank market.

However, one most obvious drawback of the balance sheet approaches is that they require extensive data on inter-institution exposures, which are usually off-balance-sheet and hard to acquire. Also, within the balance sheet framework, the modelling itself also implies the assumption of static institution behaviour (Bisias et al., 2012).

Notwithstanding, the macro-prudential supervision relies heavily on the financial network paradigm to find the connectivity of a particular node to determine its systemic importance, namely, to identify systemically important financial institutions (SIFIs) and sensitive firms, and to forecast or trace the possible contagion channels of risk and distress through a risk map showing the imbalances and exposure concentrations in the system, as opposed to the micro-prudential supervision focusing on firm-level oversight through capital requirement, on-site examination and so on. The emphasis on the network structure is reflected in several influential regulatory regimes especially after the 2008 global financial crisis (GFC), such as the Dodd-Frank Act, which imposes the requirements on financial institutions to disclose the ownership structure, major counterparties, cross-guarantees and collateral pledges, material credit exposures, etc. This type of information is critical for modelling the connecting edges in a counterparty network graph and for regulators to deter knock-on effects in the case of a single firm's insolvency and facilitate orderly resolution.

Macroeconomic indicators

Indicators and models linking systemic risk to macroeconomic conditions are, for example, He and Krishnamurthy (2014) who construct a model to distinguish between a normal state versus a systemic risk state; De Nicolò and Lucchetta (2013) who propose a GDP stress test to measure the joint dynamic of a systemic real risk indicator (the value-at-risk of the GDP) and a system financial risk indicator (the value-at-risk of the return of a large portfolio composed of financial firms) using a factor-augmented vector autoregressive model; Giesecke and Kim (2011) present a default intensity model to measure the dynamic conditional probability of failure of a large fraction of financial institutions based on a hazard model of correlated failure timing, where the authors consider the influence from past default, macroeconomic conditions, and sector-wide factors.

1.3.2 High frequency data approaches

The market-based approaches can be further divided into two main categories: portfolio models and network models (Chen et al., 2014b; Wang et al., 2018c). Many of these market data-based approaches generally require the estimation of a multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model in advance for asset returns.

Portfolio models

Stemming from measuring risk for asset portfolios, the portfolio models seek to quantify systemic risk in the financial system viewed as a portfolio composed of financial institutions. An earlier example is Lehar (2005) that proposes a portfolio approach to analyse the correlations and joint dynamics of banks' asset portfolios using stock market data. Segoviano and Goodhart (2009) also treat the banking system as a portfolio of banks and infer the banking system multivariate density (BSMD) characterized by both individual and joint asset value movements of the banks. They first use copula functions to capture the linear and nonlinear distress-dependences among banks and their endogenous changes through the economic cycle. The BSMD is then used to compute the probability of cascade effects due to a specific bank's distress, as well as several risk measures such as the Distress Dependence Matrix, the Joint Probability of Distress (JPoD) and the Banking Stability Index (BSI).

Prominent examples of portfolio approaches are Conditional Value-at-Risk (CoVaR) (Adrian and Brunnermeier, 2016), marginal expected shortfall (MES) (Acharya et al., 2017), SRISK (Brownlees and Engle, 2017), component expected shortfall (CES) (Banulescu and Dumitrescu, 2015), Distressed Insurance Premium (DIP) (Huang et al., 2009), etc. Essentially, these models share the similarity in considering co-movements of asset prices by measuring the joint distributions of asset returns and estimating cross-sectional differences in systemic risk by focusing on extreme events. The 2008 GFC demonstrates that a tail event could rapidly propagate across the market and trigger system-wide disruption and malfunctioning, implying that extreme risk matters more than simple (mean) correlations, especially for financial surveillance and regulatory purposes (Betz et al., 2016). While traditional risk measures such as value-at-risk (VaR) and expected shortfall (ES) can be used only in normal times, one fast-growing strand of systemic risk literature focuses on modelling joint distributions of extreme events and negative outcomes of a set of financial institutions, especially SIFIs.

A major difference among these models is the directionality of risk impacts or conditional events. Some methods analyse impacts of a given financial institution's extreme status on the risk of the financial system (from a bottom-up perspective), such as CoVaR measuring the system VaR conditional on a single firm being in distress (Adrian and Brunnermeier, 2016). Other models, from an opposite direction, examine which firms are most exposed when the system is in distress (from a top-down perspective), such as Shapley value (Tarashev et al., 2009), systemic impact index (SII) and vulnerability index (VI) (Zhou, 2010), MES (Acharya et al., 2017), CES (Banulescu and Dumitrescu, 2015), SRISK (Brownlees and Engle, 2017) and DIP (Huang et al., 2009). Notably, these directions of risk transmission do not reveal any causal relationship but only tail risk dependence.

Stemming from the theory in Merton (1973), the Distressed Insurance Premium (DIP) approach proposed by Huang et al. (2009) and Huang et al. (2012) measures systemic risk contributions from a creditor's perspective, based on credit default swap spreads and equity prices. Its baseline idea is to estimate the hypothetical premium a firm would have to pay to buy insurance against system-wide distress, taking into account the probabilities of default and asset return correlations of financial firms. It considers size, leverage and interconnectedness and is based on *ex ante* measures of a firm's default probability and forecast equity return correlations.

Adrian and Brunnermeier (2016) suggest that the increase in tail comovement can be used to identify systemic risk, and introduce the systemic risk measure conditional VaR (CoVaR), where VaR stands for value at risk, a commonly used risk measure for estimating potential asset value loss given a specified probability and time period. The CoVaR approach is modified by Girardi and Ergün (2013). It focuses on losses in total assets conditional on individual institution's distress, and thus measures the marginal risk contribution by a single institution to the risk of others or the whole system. The measure ΔCoVaR is defined to capture the risk component in an institution *j* that commoves with the risk of an institution *i*, thus estimating the part of systemic risk in institution *j* that can be attributed to institution *i*'s risk, namely, tail-dependence between them. It is calculated as the change in CoVaR of *j*, conditional on *i*'s return shifting from its median state to a distressed state. This approach has been largely used in empirical studies to identify SIFIs (López-Espinosa et al., 2012; Castro and Ferrari, 2014) and examine risk spillovers (Reboredo and Ugolini, 2015; Zhao et al., 2017), mainly computing CoVaR by quantile regression (Bernal et al., 2014; Härdle et al., 2016; Wang et al., 2018a), multivariate GARCH (Girardi and Ergün, 2013) or copula (Reboredo and Ugolini, 2015; Karimalis and Nomikos, 2018) models. This CoVaR method is also followed by regulatory authorities for constructing measures such as Co-Risk (IMF, 2009).

Alongside Value-at-Risk (VaR), expected shortfall (ES) is another standard institutional level risk measure conditional on the occurrence of a tail event. ES outperforms VaR in that it captures all losses beyond the threshold that VaR may fail to capture when the negative payoff is below the pre-set threshold. VaR is also not a coherent risk measure, as the VaR of the sum of two portfolios can be higher than the sum of their respective VaRs, which violates the subadditivity property. This is not a problem with ES (Artzner et al., 1999). Acharya et al. (2017) extend from the concept of ES and introduce systemic expected shortfall (SES) to measure the expected amount of an individual institution's capital shortfall in a future systemic undercapitalization event, as well as Marginal Expected Shortfall (MES) to gauge individual institutions' losses in the tail of the aggregate system's loss distribution, representing its contribution to systemic risk. The authors propose to impose an optimal taxation on each bank based on the sum of its SES and MES to internalize the external costs of systemic risk in banks. The MES model also gives rise to the idea of identifying systemically important financial institutions (SIFIs), defined as the institutions that contribute significantly to the general financial instability when they are in distress (FSB, 2010). In this line of research, Acharya et al. (2012) and Brownlees and Engle (2017) introduce the SRISK measure, which extends the idea of MES and allows to simultaneously consider the size and liability of an individual financial institution.

Banulescu and Dumitrescu (2015) use a component expected shortfall (CES) approach similar to MES and SRISK but further incorporating each firm's weight (namely, relative market capitalization) in the financial system to identify systemically risky firms. An advance of the CES approach is that it combines both the too-interconnected-to-fail (TITF) and too-big-to-fail (TBTF) paradigms, in contrast to the MES approach which privileges the TITF logic to TBTF. Moreover, CES can be easily calculated by using daily market data, as only weight of each institution is needed. As a homogenous systemic risk measure relying only on market data, CES is easier to implement and more generalizable than the SRISK measure which requires both daily market data and more complicated quarterly financial statement data (whereby we also have to assume that leverage remains constant within a given period).

Modelling network structure

While portfolio approaches such as MES and CoVaR are considered to ignore the tail risk dependence and interactions induced by the endogenous network vulnerabilities in the system (Betz et al., 2016), quantitative network methods try to detect potential inter-connectedness among financial institutions that may give rise to risk spillovers, contagion and amplification, and thus can serve to test the resilience of a network and identify systemic importance of the nodes. Prominent quantitative network methodologies using market data are, for example, the Granger-causality network (Billio et al., 2012), the vector-autoregressive (VAR) model (Diebold and Yilmaz, 2009, 2012, 2014), the tail risk interdependence network (Hautsch et al., 2014), and the tail event driven network (Härdle et al., 2016).

Within the framework of Granger causality (Granger, 1969, 1980; Granger et al., 1986), Billio et al. (2012) directly and unconditionally measure the connectedness of the financial system by using two approaches: the principle component analysis and pairwise Granger-causality tests. This method detects the commonality among asset returns to find interconnectedness among four index returns of hedge funds, banks, brokers and insurers, and to yield indirect information about systemic risk accumulation. As opposed to measures like CoVaR or MES which are conditional on simultaneous extreme losses of many financial institutions in the financial system, these measures help detect newly emerged links within the financial system during non-crisis normal periods. These measures reveal increased unconditional linkages among certain sectors in the financial systems during market prosperity, which, in contrast, are shown to be lower when gauged by aggregate correlation measures.

Diebold and Yilmaz (2009) propose to use a vector-autoregressive (VAR) model to provide separate measures of return and volatility spillovers based on forecast error variance decomposition. However, Diebold and Yilmaz (2012) argue that the methodological limitation of this framework is that it relies on the Cholesky factor identification of VARs, and the variance decompositions may thus be dependent on variable ordering. Diebold and Yilmaz (2012) overcome this problem by replacing the Cholesky factorization by the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), where variance decomposition is invariant to ordering. Diebold and Yilmaz (2014), in the same vein, model stock returns in a vector autoregressive framework to estimate directional volatility connectedness. They refine the basic VAR model of Diebold and Yilmaz (2009) to set up a network analysis, which enables them to measure systemic risk and also risk spillovers at the same time. Their VAR-based model has been widely applied in empirical studies, for example, Yarovaya et al. (2016) and Gamba-Santamaria et al. (2017). Zhang (2017) applies the Diebold and Yilmaz method to studying the dynamic relationship between oil shocks and stock market returns and finds asymmetric spillover effects between them. This VAR-based approach has also been applied to studying connectedness in commodity markets (Zhang and Broadstock, 2018), energy markets (Ji et al., 2018c; Zhang et al., 2018), housing markets (Zhang and Fan, 2018), etc.

Hautsch et al. (2014) construct a tail risk interdependence network between a set of publicly traded US financial institutions to measure financial institutions' contribution to systemic risk and monitor their systemic importance. Their approach combines the use of equity market data and balance sheet data. Based on tails of corresponding asset return distributions and using a two-stage quantile regression approach, the systemic risk contribution of an individual institution is measured as the effect of an increase in its own tail risk on the VaR of the financial system. When estimating firm-specific VaRs, the idiosyncratic firm characteristics, macroeconomic states and tail risk spillovers of other firms are all taken into account. Built on the methodology of Hautsch et al. (2014), Betz et al. (2016) quantify the marginal effect of a firm's time-varying VaR on the system's VaR to identify the tail risk dependencies and determine marginal systemic relevance of a firm in the European banking system, adopting both the two-step quantile approach and a panel fixed effects approach to tackle the dimensionality issue (Wu et al., 2019). In the same spirit of constructing a risk spillover network as Hautsch et al. (2014), Wang et al. (2017) construct an extreme risk spillover network based on a Granger causality risk test (Hong et al., 2009) and the CAViaR tool proposed by Engle and Manganelli (2004) to study the risk spillover network composed of 84 S&P 500 financial institutions during 2006-2015.

Drawn on the tail risk measure CoVaR by Adrian and Brunnermeier (2016) and network analysis model of Hautsch et al. (2014), Härdle et al. (2016) propose a semiparametric measure called TENET (tail event driven network) to study systemic interconnectedness and tail driven spillover effects in a system with higher dimensions. The identification of SIFI using this approach takes into consideration their interconnectedness structure by using two market capitalization weighted indices: the index of systemic risk receiver and the index of systemic risk emitter to measure systemic risk contributions. Different from Hautsch et al. (2014) who use a linear LASSO-based variable selection to estimate the VaR of the system, Härdle et al. (2016) employ nonlinear models to address the complexity of the financial system.

Modelling risk contagion

The idea of "excessive" spillovers is the core of contagion (Sewraj et al., 2018). For both investors and regulators, understanding risk contagion effects is equally critical to understanding systemic risk. Beyond the institutional level contagion, risks from one market/sector can spread to another market/sector, causing chain effects or contagion. Systemic risk contagion has been intensively investigated across markets and countries in empirical studies. Among others, Eichengreen et al. (2012) examine the contagion of the US subprime crisis using a principal components analysis to identify common factors in the movement of banks' credit default swap spreads. Shen et al. (2015) study the contagion effect of the European sovereign debt crisis on China's stock markets. Boubaker et al. (2016) examine the contagion between the US equity market and selected developed and emerging stock markets from 2005 to 2014, focusing on the contagion risk arising from the 2008 US subprime crisis.

It is sometimes hard to distinguish systemic risk measures and models for identifying contagion as they tend to combine together. The methodologies for capturing the network structure within the market are generally widely adopted to investigate the path of risk transmission. Forbes (2012) and Sewraj et al. (2018), among others, summarize five general strategies of modelling and testing contagion, including conditional probability analysis, correlation analysis, VAR-based models, latent factor/multivariate GARCH models and extreme value analysis (such as copula)[3]. Other network approaches can also serve as powerful tools to model contagion. Based on the pairwise Granger causality network proposed by Billio et al. (2012), Huang and Wang (2018a) build return spillover networks by Granger causality when trying to capture dynamics of systemic importance of Chinese financial institutions in 2008-2016. Sedunov (2016) compares the abilities of CoVaR, SES and Granger causality (Billio et al., 2012) in forecasting the performance of financial institutions during crisis periods around 1998 (LTCM) and 2008 (Lehman Brothers). Hong et al. (2009) propose the concept of Granger causality test of risk. Their framework is extended by, for example Candelon and Tokpavi (2016), and widely employed by, for example Corsi et al. (2018) who construct Granger-causality tail risk networks between 33 G-SIBs and 36 sovereign bonds to explore systemic risk transmission channels, and Wang et al. (2017) who propose an extreme risk spillover network to investigate the interconnectedness across 84 financial institutions in the US stock market.

We first review the vast literature using correlations of asset prices as a systemic risk indicator (Kritzman et al., 2011; Patro et al., 2013) in modelling network structure and risk contagion. In such a network, the nodes are stocks or markets, while the edges are the volatility relationships between stock prices, market indices or returns. The filtering processes employed in these studies are, for example, graph theory (Wu et al., 2019), partial correlations (Wang et al., 2018b), transfer entropy (Sandoval Junior et al., 2015) and VAR (Bekiros, 2014).

[3] Relevant surveys can be found in Forbes and Rigobon (2001).

Notably, the many specifications of the multivariate GARCH model of Engle (2002) have been employed by this large body of literature on cross-market risk contagion. Kim et al. (2015) investigate the spillover effects of the recent financial crisis on five emerging Asian countries by analyzing the conditional correlations of financial asset returns by multivariate GARCH models. Bekiros (2014) uses a bivariate skewed Student-t DCC-FIAPARCH model to capture volatility spillovers and finds evidence of asymmetry and long memory in the conditional volatility and significant dynamic correlations between the US and five BRICS stock markets from 1997 to 2013. Bonga-Bonga (2018) examines cross-transmission of financial shocks and dependence between South Africa and other BRICS economies to assess the contagion effects from 1996 to 2012 adopting a multivariate VAR-DCC-GARCH model.

Regarding the effects of the crises on cross-market correlations, Mollah et al. (2016) identify the presence of country-level contagion by a DCC-GARCH model and find evidence of contagion spread from the US to developing and emerging markets during both the GFC and the Eurozone crisis, where bank risk transfer plays a key transmission role for cross-country correlations. Bala and Takimoto (2017) use a DCC-MGARCH model with skewed Student-t density and find that stock return correlations are lower among emerging markets than among developed markets, but all increase during the GFC period, implying growing integration among markets. Syllignakis and Kouretas (2011) apply the DCC-MGARCH model to studying the time-varying conditional correlations of returns of seven emerging stock markets in Central and Eastern Europe, and find significantly increased correlations during the GFC indicating contagion of shocks from the US and Germany markets, as well as the strong explanatory power of macroeconomic fundamentals.

For the post-crisis period, Dimitriou et al. (2013) study the contagion effects of the GFC on five BRICS equity markets during 1997-2012 using a FIAPARCH-DCC framework. For most BIRCS markets, the contagion effects only emerged after the collapse of Lehman Brothers, indicating an early stage isolation or decoupling but then a recoupling. Correlations among all BRICS and US markets increase from early 2019 onwards, implying greater dependence in bullish than bearish markets. Karanasos et al. (2016) find high dynamic correlations of the stock markets and increased contagion effects between markets after crisis events, applying the vector AR-DCC-FIAPARCH model to eight national stock market returns from 1988 to 2010. Hemche et al. (2016) find that the dynamic correlations among ten developed and emerging stock markets significantly increase following the US subprime crisis, using a DCC–MGARCH model to capture the time-varying contagion and interlinkages among stock markets.

1.4 Identifying systemic importance

1.4.1 Identifying SIFI

Despite that the model-based approaches discussed above have been largely used for directly quantifying systemic risk, they sometimes may generate counter-prior results, and it is usually difficult to assess and validate these models, as it requires shrewd judgments and sufficient priors (Patro et al., 2013). An alternative, indirect way to measure systemic risk and evaluate systemic importance is to use indicator-based approaches, which rely on indicators that are believed to be highly relevant to the building-up of systemic risk and the systemic importance of a given firm.

At the firm level, Banulescu and Dumitrescu (2015) define SIFI as institutions whose failure would cause significant disruption of the financial system and detrimental effects on the broader economy, due to their size, complexity and interconnectivity. These main factors have been intensively discussed in the rich literature on evaluating the systemic importance of individual institutions and been encompassed by regulatory frameworks, giving rise to the too-big-too-fail, too-complex-to-fail and too-connected-to-fail paradigms.

Based on these logics, various indicator-based approaches have emerged to identify SIFIs. Using market data, De Nicolò and Kwast (2002) measure the degree of inter-institution dependencies by correlations of stock returns, which can be used as a systemic risk indicator, and document how consolidation activity in the financial system positively contributes to interdependency and systemic risk. Elsinger et al. (2006b) model asset correlations using stock market data and interlinkages from interbank liabilities using balance sheet data, to gauge both correlated risk exposures and mutual credit relations that may give rise to a domino effect of default. Thomson (2009) proposes to use size and the four-C criteria, namely, contagion, concentration, correlation, and conditions, to determine the systemic importance of a firm. Patro et al. (2013) use daily stock return correlations and default correlations of large US investment banks and bank holding companies and find that these correlations are simple and robust indicators of systemic risk in the market as a whole. Kritzman et al. (2011) introduce the absorption ratio to calculate the statistical connectivity within a system of financial institutions, whereby unified or tightly coupled markets indirectly indicate a higher level of systemic risk.

Acemoglu et al. (2015) introduce the concept of harmonic distance over the financial network to measure the likelihood of a bank's distress contagion and identify SIFIs. With respect to network structure, the authors find that more equally distributed interbank obligations contribute to enhancing the stability of the financial system. However, beyond a certain point, more interconnections lead to greater frangibility. Drehmann and Tarashev (2013) present two measures based on Shapley values to measure interconnection and contagion in the financial system, which help attribute system-wide risk to the contributions of individual firms and identify SIFIs for regulatory purposes. Vallascas and Keasey (2012) support that leverage restrictions, liquidity requirement, and banks' expansion indicators such as size, share of non-interest income and asset growth rate should be included in regulatory frameworks, to enhance the resilience of financial entities and reduce their vulnerability to systemic events.

The indicator-based approaches are also adopted by several well-established financial condition indices using a weighted sum of comprehensive financial indicators such as the OECD FCI (Guichard and Turner, 2008), the Bloomberg FCI (Rosenberg, 2009), the Goldman Sachs FCI (Dudley et al., 2005), or a principal components measure of indicators, such as the Federal Reserve Bank of Kansas City Financial Stress Index (Hakkio and Keeton, 2009), as well as by regulatory authorities to assess systemic importance and identify systemically important financial institutions.

Looking at the regulatory framework, the too-big-to-fail (TBTF) problem associated with SIFIs was first stated in the G20 Pittsburgh Summit in September 2009. In the 2009 joint report by the Financial Stability Board (FSB), International Monetary Fund (IMF) and Bank for International Settlements (BIS), three measures are announced to be used to identify global SIFIs, including size, lack of substitutability (indicating market importance) and interconnectedness (FSB et al., 2009).

Under the policy framework, G-SIFIs are subject to more intensive regulations commensurate with their systemic importance, including loss absorption capacity beyond the minimum of Basel III standards, recovery and resolution planning requirements, and strengthened supervision. The Basel Committee on Banking Supervision (BCBS) subsequently published its indicator-based assessment approach for identifying global systemically important banks (G-SIBs), accompanied by a bucketing approach to categorize them accordingly and additional regulatory requirements on G-SIBs (BCBS, 2011). The first list of 29 G-SIFIs was then released in November 2011 (FSB, 2011), and an updated list of 29 SIFIs alongside with new capital requirements were disclosed in July and November of 2013 (BCBS, 2013; FSB, 2013), supposed to be fully applied by the end of 2019.[4] Following the banking sector, the International Association of Insurance Supervisors (IAIS) published the initial indicator-based assessment methodology of G-SIIs in 2013 (IAIS, 2013) and an updated version in 2016 (IAIS, 2016) to guide the assessment of systemic importance of global insurance firms.

1.4.2 Macro-prudential regulations

In terms of macroprudential regulatory tools imposed on SIFIs, levying tax on systemic risk-taking of financial institutions has been proposed by many scholars to safeguard financial stability. Gai et al. (2011) suggest a tax on SIFIs commensurate with their systemic risk contribution, in response to the too-connected-to-fail problem. Biais et al. (2010) and Freixas

[4] The list will be updated annually, and the methodology and indicators will be reviewed every three to five years. Benoit et al. (2018) review the pitfalls of the SIFI scoring system. Moenninghoff et al. (2015) review the trade-offs of the G-SIB regulations. Bongini et al. (2015) study the market reactions and wealth effects of introduction of the new SIFI regulations introduced by FSB and BCBS, including the disclosure of identifying methodology on 19 July 2011, the publications of the first list of SIFIs on 4 November 2011 and then an updated list on 1 November 2012. They find a common positive market reaction to the first event and differing effects of the second depending on firm-level capital adequacy and business models. The third event received no statistically significant market reaction, implying a diminishing effect of the construction of the regulatory framework as it proceeded.

and Rochet (2013) study the dynamic moral hazard problem that SIFI owners encourage excessive risk-taking of management as tail risks are usually unobservable to investors, and present solutions such as levying systemic risk tax as insurance against systemic shocks. Acharya et al. (2013) also propose to impose a systemic risk tax on individual financial firms based on their marginal risk contributions, computed by the method in Acharya et al. (2017). Markose et al. (2012) suggest to levy a Pigovian tax on SIFIs identified by network centrality measures, which is also proposed by Korinek (2011), so as to internalize the risk of banks' decisions and correct banks' incentives of systemic risk-taking.

With respect to capital requirement, while Cecchetti (2015) suggests higher capital requirements with less changes over time to be imposed on financial institutions to promote a resilient financial system, some studies argue that capital regulations on financial institutions can also induce unintended consequences and increase market risk. As mentioned in Section 1.2.5, this type of regulations could pose unintended challenges to maintain financial stability, especially when the system is experience turbulences (Brunnermeier and Pedersen, 2009; Benoit et al., 2015; Merrill et al., 2013). To satisfy risk-sensitive capital requirements such as those stipulated in the Basel Accord of 1988, banks may tend to sell low risk assets rather than high risk assets even at fire-sale prices, accelerating the forming of systemic risk. It is also argued that higher capital reserves may play a role in entailing tail risk-taking, as the seemingly enhanced buffering function of the capital reserve alleviates the concerns of breaching the regulatory requirements on minimum capital ratio (Perotti et al., 2011). Aiyar et al. (2014) find that the increase in capital requirement has a significant negative effect on UK banks' cross-border credit supply. The effect of imposing capital requirement and its interaction with other regulations are also studied in, for example, Tirole (2011) and Goodhart et al. (2013).

While the traditional micro-prudential supervision is mainly concerned with individual firms' performance as shown in their balance sheets and liquidity ratios with the belief that firms with higher level of leverage are more vulnerable to financial shocks, Papanikolaou and Wolff (2014) find that deleveraging thus benefits the financial health of individual firms but is detrimental to the financial stability of the whole system. Vallascas and Keasey (2012) argue that regulatory frameworks imposing leverage restrictions and liquidity requirement can be useful for increasing the resilience of financial entities and reducing their vulnerability to systemic events, but critical elements such as size, share of non-interest income and asset growth rate are also key determinants of risk exposures, whose importance, however, is understated in the existing regulatory framework. Regulations regarding liquidity and stress tests are discussed in, among others, Perotti et al. (2011), Bouvard et al. (2015) and Bianchi and Mendoza (2018).

1.5 Conclusions

In response to regulatory and institutional changes and technological development in the financial system, financial institutions seek to create new products, broaden and diversify their business and services (Papanikolaou and Wolff, 2014). With the evolution and developing trends in the financial system, many new issues arise and pose challenges to the global financial stability.

First, the ongoing financial liberalization incentivizes more risk-taking of financial institutions through increased market competition in developing economics and new opportunities in developed economies, indicating that the institutional environment also matters (Cubillas and González, 2014). Besides the institutional environment, market competition also plays a role in affecting systemic risk. While increased competition motivates firms to diversify their risk and therefore indirectly reduce vulnerability of the system, banks located in countries with weak private monitoring, more state-ownerships and policies suppressing competitions are found to be more fragile (Anginer et al., 2014).

On the other hand, financial innovation, including the proliferation of financial instruments (Caccioli et al., 2009), securitization and shadow banking activities (Acharya and Richardson, 2009; Battaglia and Gallo, 2013; Gennaioli et al., 2013), facilitates aggregate risk-taking and therefore increases the likelihood of financial institutions being more systemically risky, as investors find it harder to monitor risk due to complexity inherent in the process of securitization (Simkovic, 2013).

Furthermore, against the backdrop of increasing financial integration and globalization, Ghosh (2016) finds that the participation of foreign banks in the local market helps deter the occurrence of banking crises and bolster financial stability. Castiglionesi et al. (2017) find that a higher level of financial integration helps reallocate liquidity and smooth local shocks, which leads to more stable interbank interest rates during normal times, but greater interest rate spikes during crises due to decreased aggregate liquidity holdings. The financial integration and globalization related to real activity are also analysed by De Nicolò and Juvenal (2014).

Motivated by the extant empirical studies and facing these issues and new trends in financial markets, we proceed to investigate our research questions focusing on the systemic importance of financial market components as well as financial market integration, in the following three main chapters. We hope that these studies contribute to the proliferation of the related literature and the progress of policy designs regarding curbing systemic risk in financial markets.

2 Identifying systemically important sectors in China's stock market

This chapter investigates the question of how much each sector contributes to systemic risk in the Chinese stock market[5]. Based on two recently developed approaches, namely, Marginal Expected Shortfall (MES) and Component Expected Shortfall (CES), the empirical results demonstrate that weights of sectors matter. Moreover, Financials, Industrials and Energy sectors are found to be the top risk contributors, although their contributions tend to evolve over time. The results have strong implications to both investors and regulators for risk management and regulatory purposes.

[5] Chapter 2 is based on a published article (Wu, 2019a) in *Finance Research Letters*, 2019, 31, 386-390.

2.1 Introduction

The impacts of the 2008 global financial crisis are profound and long-lasting. Following the federal takeover of Fannie Mae and Freddie Mac, the failure of Lehman Brothers on 15 September 2008 soon spread risk across the financial system and led to distress and failures of several big institutions[6] and many other smaller banks over the next days or weeks. Extreme losses of these key financial institutions have shown the tendency of spreading across the whole financial system and leading to system-wide instability and broader crises, severely threatening the normal functioning of the financial system (Sedunov, 2016).

The failures of the key financial institutions during the crisis have incurred enormous social costs on bank bail-outs and rescues for curbing further risk contagion and preventing collapse of the whole system. Notable examples are large government expenditures in the form of huge stimulus packages to head off recession as well as financial reforms and legislations in the aftermath of the 2008 crisis, such as the US Troubled Assets Relief Program (TARP) enacted by the Bush administration in 2008 and the Dodd-Frank Act by the Obama administration in 2010.

Neglecting systemic risk and its contagious effects can induce generalized malfunctioning the financial system, destabilize regional, national and even global economy, and eventually undermine overall social welfare. Compared to the huge *ex post* costs spent on rescue and recovery, taking *ex ante* precautious measures by curbing systemic risk contagion is believed

[6] Among others, AIG, Bear Stearns, Merrill Lynch, Citigroup, Bank of America, Morgan Stanley, Goldman Sachs, Washington Mutual, and Wachovia.

to be much more efficient and effective, and sufficiently reduce the possibility of a system-wide collapse and costs following it.

Following the GFC, there has emerged a surge of literature and a diversity of policy frameworks generally seeking to shuffle the regulating of systemic risk from *ex post* recovery to *ex ante* regulation, by identifying three important contributors to the building-up of systemic risk: particular shocks to the financial system such as asset price misalignments; early warning signals that impend threats to financial stability; and underperforming policies and unintended consequences (Bisias et al., 2012). According to Acharya et al. (2012), a most critical issue for improving regulation and curbing systemic risk from materializing and jeopardizing the system is to identify the biggest contributor(s) to systemic risk and its spillover effects, namely, the systemically important financial institutions (SIFIs). This gives rise to several prominent regulatory measures, such as those defined and adopted by the Basel Committee on Banking Supervision (BCBS) in identifying G-SIBs (BCBS, 2011). By effectively regulating SIFIs during normal periods, the possibilities of risk escalation can be reduced before it can lead to system-wide meltdown. Academic researchers have proposed several methodologies for measuring systemic risk and modelling contagion.

This study is closely related to the stream of literature of measuring systemic importance of each component in a system. Specifically, we adopt two systemic risk measures, Marginal Expected Shortfall (MES) (Acharya et al., 2017) and Component Expected Shortfall (CES) (Banulescu and Dumitrescu, 2015), to investigate the systemic risk contributions made by sectors in the Chinese stock market. Extending from the general ideas of the MES and CES approaches, this research attempts to extend the concept of systemic risk, which has been extensively studied in the setting of the financial system, to the Chinese stock market, from institutional-level risk contribution to sectoral risk contribution. It is primarily motivated by the argument that investors usually tend to rely on not only market but also sector-specific indices as an important reference to evaluate and forecast portfolio performance (Ewing, 2002; Ewing et al., 2003). Information transmissions within and across sectors have important implications for both investors and regulators (Wang et al., 2005). In a recent empirical study, Wu et al. (2019) investigate systemic risk and sectoral risk spillovers in the Chinese stock market, focusing on correlation structures and inter-connectedness across sectors in the market.

Following this line of research but paying more attention to tail co-movements, this research studies the systemic importance of sectors in the Chinese stock market in the post-global financial crisis period, and compares the performance of time-varying MES and CES approaches. This study makes the following contributions to the literature. First, in the spirit of identifying systemically important financial institutions, it extends systemic importance measures from institutional level to sectoral level, and from the financial system to the stock market, which offers a variant and broader perspective on analyzing systemic importance and risk transmission channels. Considering the significant importance of the stock market to the long-run sustainable economic growth, it is crucial to maintain its efficient functioning and stability. One most effective way is to understand how systemic risk develops and evolves over time in the stock market, and more importantly, the pattern with which risk tends to spread across sectors.

Second, this study seeks to focus on the post 2008 financial crisis period in China’s stock market, during which there have been several severe market crashes hurting both investors’ confidence and the broader economy. Shadowed by the 2008 global financial crisis, however, relevant studies are largely missing. Third, by identifying the most important sectors in extreme events, this study intends to send important messages to both investors and regulators. Knowing which sectors contribute the most to systemic risk or are more susceptible to systemic risk enables investors to better allocate and diversify their portfolios across sectors to reduce the level of aggregate risk exposure of the portfolio. On the other hand, it helps regulators target the systemically most important sectors and effectively curb the aggregate risk in the whole market.

The remainder of the chapter is organized as follows. In Section 2, we review the relevant literature on systemic risk including the research focusing on the Chinese market. In Section 3, we introduce the methodologies used in the empirical application, including MES and CES. In Section 4, we present the data and discuss the empirical results. Section 5 summarizes the empirical results and concludes with some policy and investment implications.

2.2 Literature review

Since the global financial crisis, identifying and regulating SIFIs is central to many famous regulatory frameworks. Alongside with regulatory updates, academics have proposed various tools for identifying systemically important institutions (SIFIs) and the contagion mechanism, so as to develop early warning indicators of systemic risk, either in a single country context (for example, Hmissi et al., 2017), or in a global context. Motivated by the idea of identifying firm-level systemic importance (for example, Hmissi et al., 2017), this study extends its scope to sectors and seeks to identify sectoral systemic importance in the Chinese stock market. The literature related to identifying and regulating SIFIs, sectoral systemic importance and systemic risk in the Chinese stock market is accordingly reviewed here.

To serve the purpose of capturing timely information and enhancing forecast power of risk dynamics, this study adopts the model proposed by Acharya et al. (2017) and Banulescu and Dumitrescu (2015) using high-frequency stock market data, following the vine of market-based approaches. Our adoption of risk measures also categorizes our study to the literature focusing on quantitatively measuring tail risk contribution. An additional reason of using market data rather than supervision or accounting data in this study is due to the skeptical views on the credibility of accounting data and official statistics in China, where political or economic forces may lead to compromised data transparency and reliability (Ball, 2016; Plekhanov, 2017). Thus, using market data generated by real-time transactions is more likely to facilitate an objective and transparent analysis on systemic risk in the Chinese market.

2.2.1 Sectoral risk contributions

Besides the literature on estimation of systemic importance of firms, this study is also closely related to the vine of research investigating systemic risk contributions of sectors and cross-sector risk spillovers. Systemic importance can be measured not only at individual firm level, but also at sector level, to depict a picture of the systemic risk hierarchy for financial regulatory and supervision purposes. Moreover, identifying sectoral heterogeneity in systemic risk contribution is highly relevant to facilitating macro-prudential regulating of curbing risk contagion, as the idea of "excessive" spillovers is the core of contagion (Sewraj et al., 2018), and risk spillovers can occur not only across institutions, but more widely across sectors, markets and countries, causing a broader range of chain effects.

A large body of literature has examined cross-market and cross-country risk contagion. Eichengreen et al. (2012) study the contagion of the US subprime Crisis to the global banking system by a principal components analysis to identify common factors in the movement of banks' credit default swap spreads. Boubaker et al. (2016) use the Granger causality test to study the contagion between the US equity market and selected developed and emerging stock markets from 2005 to 2014, focusing on the contagious risk arising from the 2008 subprime crisis in the US. Sandoval Junior et al. (2015) study 83 international market indices to detect the information flow between market indices and construct a dependency network based on partial correlations.

Research related to sectoral contribution to systemic risk mainly focuses on heterogeneity in sectoral performances and volatility spillovers among equity sectors. Ranjeeni (2014) finds that sectoral performances were heterogeneously affected by the release of negative news during the crisis period, using the release of Lehman Brothers' bankruptcy news for an event study. The author examines 481 firms during the bankruptcy period, and finds that among sectors in the New York Exchange (NYSE) and financial industries, the financial sector and the diversified financial industry were most significantly affected by the Lehman Brothers episode, which had higher levels of exposure to the Lehman Brothers. Hammoudeh et al. (2009) study the dynamic volatility and volatility transmission in the three main sectors (Service, Banking, and Industrial) in four Gulf Cooperation Council (GCC) countries using a VAR-GARCH model. The authors provide evidence of moderate volatility spillovers between sectors in each country except Qatar. Based on the models' results, they further calculate and propose optimal weights and hedge ratios for two-sector holdings for each GCC country. Meric et al. (2008) investigate the co-movements of sector indices in five developed markets of the UK, US, Germany, France and Japan, in both bull and bear periods, using principal components analysis and Granger causality tests. Their findings provide practical suggestions on portfolio diversification to investors in both bull and bear markets. Zheng et al. (2012) use the growth rate of the principal components of the correlation matrix of 10 Dow Jones economic sector indices as an indicator of systemic risk.

Considering the network topology, Wang et al. (2017) construct an extreme risk spillover network and study the risk spillover network composed of 84 S&P 500 financial institutions belonging to four sectors. The static and dynamic network analyses for 2006-2015 find that on average the real estate and bank sectors are net extreme risk senders, while insurance and diversified financial sectors are net receivers, with varying network topologies shown in the 2008 GFC and the European sovereign debt crisis periods. Buccheri et al. (2013) investigate the monthly dynamics of correlations among 49 industry indices of in the US stock market and construct a correlation-based network during 1969-2011. Fast variations in the first and second eigenvalues of the correlation matrix are found during the dot-com bubble and the subprime crisis periods. Djauhari and Gan (2016) construct a network of the NYSE sectors by vector correlations. Yang et al. (2016) study the information flow in the network constructed by trading volume correlations among sectors in the US stock market.

Eckernkemper (2018) proposes an approach based on a dynamic two-component mixture copula and marginal expected shortfall to model the dependence structure between market and institution returns. The empirical analysis of Dow Jones Industrial Average components in 2000-2014 shows that individual risk contributions by institutions depend highly on their sectoral affiliations. Risk contributions vary across sectors, with sector Financials followed by Industials and Materials having the highest risk contribution, while sector Consumer Staples followed by Health Care having the lowest.

2.2.2 Systemic risk in China's financial system

Among the studies of systemic risk in the Chinese market, the Chinese banking system has been relatively more explored. Based on the Basel Committee approach, Chen et al. (2014b) propose an indicator-based approach to identify the domestic systemically important banks in China. Using copula functions, the authors detect the changes in the correlations between D-SIBs and non-D-SIBs and systemic importance of individual banks. Wang et al. (2015) use the Merton Model and study the default correlations among Chinese listed banks between 2007 and 2011.

From a network perspective, Wang et al. (2018c) document the high interconnectedness among 14 listed banks in the Chinese banking system between 2008 and 2016, employing the volatility spillover network proposed by Diebold and Yilmaz (2014). In their sample, state-owned banks contribute the least to volatility connectedness, while city commercial banks contribute the most. Based on the Granger causality network approach of Billio et al. (2012), Huang and Wang (2018a) build return spillover networks and try to capture the dynamics of systemic importance of Chinese financial institutions from 2008 to 2016.

Other studies fall in the vine of portfolio approaches. Huang et al. (2016) measure the systemic risk contribution of Chinese financial institutions by CoVaR estimated by a dynamic conditional correlation multivariate GARCH (DCC-MVGARCH) model, using daily stock market data in 2011-2015. They find greater risk contributions made by small and medium-sized commercial banks than their bigger counterparts. They also analyse the network topology using a minimum spanning tree constructed by dynamic conditional correlations to find further evidence of risk contribution. Fan et al. (2017) examine 13 listed commercial banks in China between 2010-2016, using an indicator-based method employing balance sheet data to measure systemic importance and then CoVaR computed by quantile regression to find the risk spillover effects among them. They also find that not only large banks but also smaller ones make significant risk contributions. Xu et al. (2018) adopt CoVaR estimated by a DCC-MIDAS model with student-t distribution to measure systemic risk in the Chinese banking system. Their model also includes macroeconomic variables to directly estimate systemic risk. Huang et al. (2017) compare four systemic risk measures including CoVaR, MES, the systemic impact index (SII) and the vulnerability index (VI) (Zhou, 2010) when examining the systemic risk of 16 listed banks in the Chinese banking sector between 2007 and 2014 using equity prices, and find that while these measures capture different aspects of systemic risk and exhibit different patterns, they deliver the significantly correlated rankings of the systemic importance of banks[7]. Fang et al. (2018b) combine five popular systemic risk measures including leverage ratio, SRISK, VaR, ΔCoVaR, and CAPM-β×MV, using a principal components model, to investigate systemic risk in the Chinese banking industry between 2010 and 2016.

Another strand of literature focuses on systemic risk in the broader financial system in China. Huang and Wang (2018b) study the systemic importance of financial institutions in Chinese stock market using a VAR-MAGARCH model to construct volatility spillover networks and using network centralities to measure systemic importance. In their sample of 31 publicly traded Chinese financial institutions between 2008 and 2017, those with larger sizes and higher asset growth rates tend to be more systemically important. Gang and Qian (2015) study the impact of domestic monetary policies on systemic risk in China during 2008 and 2013 after the Lehman Brothers collapse using a structural vector autoregressive model, where systemic risk is

[7] Sedunov (2016) compares the abilities of CoVaR, SES and Granger causality (Billio et al., 2012) in forecasting the performance of financial institutions during crisis periods around 1998 (LTCM) and 2008 (Lehman Brothers), and find that the modified CoVaR method outperforms the other two.

measured by a common factor decomposed from the variance of monthly MES of Chinese publicly listed financial institutions. The authors find significant influences from both global market volatility and domestic monetary policy shocks, showing the importance of prudent monetary policies. Wang et al. (2018a) examine the interconnectedness among 24 publicly traded Chinese financial institutions between 2008 and 2016 by a tail-event driven network (TENET) approach proposed by Härdle et al. (2016), and find that large commercial banks and insurers show systemic importance, while small firms with high connectedness are also systemically important. Fang et al. (2018a) construct a tail risk network based on CoVaR to estimate the overall systemic risk in the Chinese financial system by employing the LASSO method, and find that firm's idiosyncratic risk is mainly driven by risk spillovers from its connected firms.

2.2.3 China's stock market and sectoral systemic risk

The Chinese stock market, alongside its general success, has often been considered a very risky investment arena, reflected by low returns and high volatility (Su and Fleisher, 1998). Stock prices in China have frequently experienced booms and crashes since the very early stages of the market, referred to as a "casino manipulated by speculators", quoting from a preeminent Chinese economist Jinglian Wu in 2001.

Having been subject to on-going reforms and increasing exposures to risk spillovers form the global economy and international market shocks (Glick and Hutchison, 2013; Mensi et al., 2016; Yu et al., 2017; Zhang, 2017; Yao et al., 2018), the market has been fast evolving with constantly changing and sometimes wobbling market conditions. The recent years, especially after the 2008 global financial crisis, have witnessed especially high volatility in stock prices and more frequent and server market crashes, notably, the crashes around August 2009 and the more recent and drastic one combining two major crashes and successive smaller ones from June to September 2015 (Wu et al., 2019). The Shanghai Composite index slumped from 5176 on 15 June 2015 to 2850 on 26 August 2015, and China Securities Index (CSI) 300 index from 5362 to 2952, with roughly 3.5 trillion USD equivalent market value evaporated. During the massive crashes, for several times thousands of stocks hit the daily price-dropping limit within one trading day. The adverse effects of the crashes continued haunting the stock market for a long period afterwards. There were totally 16 times within the following seven months when thousands of stocks' prices plummeted by 10% (which is the daily price changing limit) within one day. Strongly affected by the on-going trade war between China and the US, 2018 also marked one of the worst years for the Chines stock market, with the Shanghai Composite Index dropping down by more than 20% in the year and the country's industrial sector seriously hit. After a massive market crash, it usually takes a long time for investors and the market to recover, causing long lasting detrimental influences on both the stock market itself and the overall macro economy.

The extant literature on sectoral systemic importance in the Chinese stock market mainly focuses on the network topological features. Wu et al. (2019) investigate sectoral risk contributions and inter-sector dependence in the Chinese stock market using correlation and graph theory, and corroborate their graphic evidence by the VAR model proposed by Diebold and Yilmaz (2014). Feng et al. (2018) use the volatility spillover effects to build a directional sector network in the Chinese stock market using a GARCH-BEKK model and the Wavelet method (Percival and Walden, 2006) to decompose sector index series into different time scales. The minimum spanning tree and hierarchical tree are used to detect the central nodes in the sectoral network in China stock market, constructed by such as Pearson correlation coefficient (Yang et al., 2014) and the DCC-GARCH model (Qiao et al., 2016), where network stability and clustering effects among sectors are examined. Mai et al. (2014) use a partial correlation planar maximally filtered graph method to build up two directed networks for the CSI 300 stocks and the constituent sectors, respectively, and find the dominance of the industrial sector over other sectors, and a quarterly stability of inter-sector influence. Hao and He (2018) detect the univariate dependence among manufactory, finance and real estate sectors in the Chinese stock market by empirical copulas using sector indices from 2000 to 2014 and find evidence of linkages among these three sectors.

Motivated by these sectoral studies, this research seeks to use sectors in the stock market as the unit of interest to study how risk contagion works in the China market, and to identify the systemically important sector(s) (SIS) in the Chinese stock market. Rather than focusing on the network topology, this study uses portfolio approaches to evaluate the systemic importance of sectors in the Chinese stock market by adopting two recently developed measures, MES and CES. To the best of our knowledge, sparse studies have considered the sectoral risk contribution in the Chinese stock market from this perspective.

Our adoption of the Chinese dataset also accounts for the growing importance of the fast internationalized and liberalized Chinese equity market to global financial stability (Glick and Hutchison, 2013; Zhang, 2017; Yao et al., 2018), and the increasing integration and impacts between the global markets and the Chinese market (Shen et al., 2015; Boubaker et al., 2016). Despite unprecedented economic growth in the past decades, the country's economy has been facing perpetuating problems such as outsize debt expansion, housing bubbles (Zhang et al., 2017; Zhang and Fan, 2018), excess industrial capacity against tepid demand, and new challenges such as slowdown in growth and increasing economic policy uncertainties in the wake of the US-China trade war (Zhang et al., 2019). These have led to mounting anxiety and fear of a financial calamity, which may not take the same course as, for example, the Lehman Brothers episode, due to China's unique political, economic and legal attributes, but can inflict no less damage on domestic economy and threaten global financial stability. Furthermore, compared to some previous studies focusing on a specific crisis, several recent market crises periods in the Chinese stock market are covered by our sample period. Our empirical evidence shows that during these turmoil periods, risk spillover effects within the system were drastically amplified.

2.3 Methodology

2.3.1 Systemic risk measures

In this study, we adopt two systemic risk measures, MES and CES, to identify the systemic risk contribution of each sector in the Chinese stock market. Such measures enable us to decompose the overall risk in the system into individual components' risk contributions through a portfolio risk analysis that views the whole market as a portfolio and its constituent sectors as portfolio assets. MES and CES have advances over another prominent measure SRISK in two regards. First, both MES and CES are homogenous systemic risk measures requiring only market data to compute them. By contrast, the SRISK measure requires using both market and balance sheet data, which causes the friction arising from different data frequencies. Also, using MES and CES instead of SRISK, we no longer need to assume that the leverage ratio remains stable for a given period of time. Based on these advances of MES and CES, this study opts for these measures to analyse the sectoral contributions to systemic risk in the Chinese stock market.

MES

Value-at-Risk (VaR) and expected shortfall (ES) are two popular measures of potential losses in an extreme event. Given a confidence level $1 - \alpha$, VaR measures the most that a firm loses with that confidence, i.e., the value of return R that satisfies $\Pr(\mathrm{R} < -\mathrm{VaR}_\alpha) = \alpha$, whereas α is typically set to be 1% or 5%. ES is the expected loss conditional on the return being less than the α quantile, equivalent to conditional on loss being greater than VaR_α, giving the definition of $ES_\alpha = -\mathrm{E}(\mathrm{R}|\mathrm{R} < -\mathrm{VaR}_\alpha)$. ES thus measures the average loss conditional on the loss being greater than the VaR.

Comparing the two risk measures, ES has advantages over VaR in two regards. First, VaR may fail to capture potential tail losses which are below the 1% or 5% threshold. By contrast, ES is able to capture all losses beyond the threshold. VaR is also not a coherent risk measure, as the VaR of the combination of two portfolios can be higher than the sum of their respective VaRs. This violates the subadditivity property, which is not a concern with ES (Artzner et al., 1999).

Extending from ES rather than VaR based on the above reasons, Acharya et al. (2017) consider the return of a bank, R, which is the combined result of its individual groups or trading desks, as a weighted sum of each group *i*'s return. We extend the basic idea of a bank to a stock market index, which is the weighted sum of all sectors' returns at time *t*:

$$r_{mt} = \sum_i w_{it} r_{it} \tag{2.1}$$

where r_{mt} denotes the aggregate stock market return at time *t*; w_{it} is the weight and r_{it} is the return of sector *i* at time *t*.

The ES measures the expected loss in the stock market conditional on the aggregate market return being less than the α quantile (i.e. VaR_{α}). The conditional ES (with respect to past information) for the stock market is defined as:

$$ES^{\alpha}_{m,t-1} = -\mathbb{E}_{t-1}(r_{mt}|r_{mt} < -\mathrm{VaR}_{\alpha})$$

$$= -\sum_{i=1}^{n} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < -\mathrm{VaR}_{\alpha}) \tag{2.2}$$

Each sector's marginal contribution to the overall systemic risk is defined as the marginal expected shortfall (MES), and computed as the first order derivative of the market's expected shortfall with respect to the weight of the *i*th sector:

$$\mathrm{MES}^{\alpha}_{it} \equiv \frac{\partial ES^{\alpha}_{m,t-1}}{\partial w_{it}} = -\mathbb{E}_{t-1}(r_{it}|r_{mt} < -\mathrm{VaR}_{\alpha}) \tag{2.3}$$

Following the logic of Acharya et al. (2017) where MES measures each group's risk-taking to the bank's overall risk, marginal expected shortfall is calculated for each sector *i* to represent its marginal contribution to the market-wide systemic risk, when we let R be the return of the aggregate stock market. Said differently, $\mathrm{MES}^{i}_{\alpha}$ measures the average return of sector *i* on days when the stock market return drops below the threshold VaR_{α}. In this study, the quantile α is set to be 5%.

CES

Banulescu and Dumitrescu (2015) suggest that the weight of each component in the system should be considered when evaluating the relative importance of the component to the total systemic risk. They propose the concept of component ES (CES), which can be written as:

$$\text{CES}_{it}^{\alpha} \equiv -w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < -\text{VaR}_{\alpha}) \tag{2.4}$$

From the expression in equation (2.4), CES is the product of MES and the weight of the sector in the stock market. While MES calibrates the marginal contribution of a sector to the systemic risk in the market, CES quantifies the absolute risk contribution of a sector by adding in the weight component (Banulescu and Dumitrescu, 2015). A higher value of CES therefore indicates greater risk contribution and more systemic importance of a sector. Another advantage of introducing the weight in is that the expected loss of the whole stock market equals the sum of all sectors' CES, and CES for each sector can be expressed as a percentage of the ES of the whole market:

$$ES_{m,t-1}^{\alpha} \equiv \textstyle\sum_{i=1}^{n} CES_{it}^{\alpha} \tag{2.5}$$

In this study, the weight is set to be the relative market capitalization of the sector. It represents the relative size of the sector in the stock market and thus addresses the TBTF logic. It is also an element in equation (2.1) of computing the stock market return, which will be used for estimating conditional correlations, innovations and tail expectations. Following Banulescu and Dumitrescu (2015), we adopt the methodology of hypothetical returns widely used in portfolio analysis. At each date, the past hypothetical market returns are defined by using the current weights of the sectors[8]. This adoption of weight assumes that the composition of the stock market (measured by the weights of sectors) remains unchanged during this period, thus enabling us to find the systemic risk contribution of a given sector without the influence from compositional changes. Alternatively, the weight can also be flexibly defined by the regulators

[8] The in-sample weights can alternatively be defined as historical relative market capitalization. Returns computed by these weights are therefore actual returns rather than hypothetical returns. This weighting scheme is used by for example, Brownlees and Engle (2012) and Acharya et al. (2010).

to account for other potentially important indicators of the sector's risk contribution, such as leverage and size.

CES%

Following Banulescu and Dumitrescu (2015), a percentage version of CES, or CES(%), is also used, which equals the percentage of a given sector's CES out of the sum of all sectors' CES, or the market's ES:

$$CES\%_{it}^{\alpha} = \frac{CES_{it}^{\alpha}}{\sum_{i=1}^{n} CES_{it}^{\alpha}} \times 100 = \frac{CES_{it}^{\alpha}}{ES_{t-1}^{\alpha}} \times 100$$

$$= \frac{w_{it}\mathbb{E}(r_{it}|r_{mt} < -\mathrm{VaR}_{\alpha})}{\sum_{i=1}^{n} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < -\mathrm{VaR}_{\alpha})} \times 100 \qquad (2.6)$$

This CES% measures the proportion of the systemic risk attributed to sector *i* at time *t*. By construction, the CES% of each sector should add up to 100%, which can thus simplify the interpretation of the risk contribution made by each sector. Once the weight is defined and the conditional ES is obtained, the CES% can be immediately calculated.

2.3.2 Estimation

We conjecture that leverage effects exist in the return series, where volatility increases more following a large price fall relative to a price rise of the same magnitude. We therefore adopt the DCC-GJR-GARCH (1,1) model to estimate MES and CES for sectoral returns. Banulescu and Dumitrescu (2015) provide a detailed procedure to estimate MES and CES using the dynamic conditional correlation (DCC) model with a GJR-GARCH (1,1) process for each individual series. Following Banulescu and Dumitrescu (2015), there are three steps for estimating MES and CES, shown as follows.

DCC-GJR-GARCH estimation

We first consider a bivariate GARCH model for the demeaned return processes in a simple market model (CAPM) with time-varying conditional betas (Engle, 2016):

$$r_t = H_t^{1/2}\epsilon_t \tag{2.7}$$

where $r_t = (r_{mt}\ r_{it})'$ is the vector of the stock market and sector returns; $\epsilon_t = (\varepsilon_{mt}\ \xi_{it})'$ is the vector of innovations, independently and identically distributed with zero mean and an identity covariance matrix; H_t is the time-varying conditional variance-covariance matrix defined as:

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\sigma_{it}\rho_{it} \\ \sigma_{mt}\sigma_{it}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{2.8}$$

where σ_{mt} and σ_{it} denote the conditional standard deviations for the market and sector returns at time *t*, respectively; ρ_{it} denotes the conditional correlations at time *t*. This specification indicates that the linear dependence between the sector and market returns are fully captured by the time-varying conditional correlation ρ_{it}. These elements in the H_t matrix are estimated in this first step, following the two-stage estimation procedure advocated by Engle (2002).

Stage 1. In the first stage, each series of market or sectoral returns is modelled separately as a univariate GJR-GARCH (1,1) specification proposed by Glosten et al. (1993), to obtain conditional volatility for all return series and the standardized residuals of returns. The GJR-

GARCH specification is used as it captures the asymmetric behavior of the conditional variances, as the financial time series exhibit fat tails and excessive kurtosis. The GJR-GARCH (P, Q) models for the market and sectoral conditional variances are respectively given as:

$$\sigma_{mt}^2 = \omega_m + \sum_{j=1}^{Q} \alpha_j r_{m,t-j}^2 + \sum_{p=1}^{P} \beta_p \sigma_{m,t-p}^2 + \sum_{j=1}^{Q} \gamma_j I_{t-j} r_{m,t-j}^2 \tag{2.9}$$

$$\sigma_{it}^2 = \omega_i + \sum_{j=1}^{Q} \alpha_j r_{i,t-j}^2 + \sum_{p=1}^{P} \beta_p \sigma_{i,t-p}^2 + \sum_{j=1}^{Q} \gamma_j I_{t-j} r_{i,t-j}^2 \tag{2.10}$$

where $I_{t-j} = \begin{cases} 1\ if\ r_{t-j} < 0 \\ 0\ otherwise; \end{cases}$ ω is the constant; α, β and γ are the model parameters. To satisfy non-negativity of the conditional variance, the constraints of model parameters are that $\omega > 0$, $\alpha_j > 0$, $\alpha_j + \gamma_j \geq 0, \beta_p \geq 0$ for $\mathrm{j} = 1,2, \ldots, \mathrm{Q}$ and for $\mathrm{j} = 1,2, \ldots \mathrm{P}$, while $\alpha_j + 0.5\gamma_j + \beta_p < 1$ for stationarity of σ_t^2. For a leverage effect indicating that volatility rises more after a large negative shock than a large positive shock of the same magnitude, we would expect to see a positive sign of the asymmetry term, i.e., $\gamma_j > 0$. Q is the number of lags of the ARCH component. P is the number of lags of the GARCH component. The model parameter set is estimated by QMLE for each return series to generate consistent and asymptotically normal estimators without making prior distribution assumptions of the innovations. The joint log-likelihood function of this stage is constructed by summing up the log-likelihoods of individual univariate GARCH models. When the parameter set is estimated, the conditional variances can be obtained for each series, as well as the standardized residuals, defined as:

$$\epsilon_t = D_t^{-1} r_t \tag{2.11}$$

where D_t is a diagonal matrix containing the conditional standard deviations on the leading diagonal, which are the square roots of the conditional variances σ_{mt}^2 and σ_{it}^2 from the univariate GJR-GARCH estimation on each series using equations (2.9) and (2.10). As $\epsilon_t = (\varepsilon_{mt}\ \xi_{it})'$, we thus have $\varepsilon_{mt} = D_{mt}^{-1} r_{mt}$ and $\xi_{it} = D_{it}^{-1} r_{it}$, which are the standardized residuals for the market and the *i*th sector, respectively.

Stage 2. In the second stage, we estimate the time-varying conditional correlation, ρ_{it}, for each pair of market-sector returns, using a dynamic conditional correlation (DCC) model based on univariate conditional variances for all series obtained by equations (2.9) and (2.10). The DCC model proposed by Engle (2002) allows multivariate modelling of high-dimensional data samples and considers the autocorrelation of variables, thus allowing us to capture the time-varying conditional correlations between the market and sectoral returns. In the DCC framework, the time-varying conditional variance-covariance matrix H_t is decomposed as:

$$H_t = D_t R_t D_t \tag{2.12}$$

where R_t denotes the symmetric conditional correlation matrix of the standardized residuals ϵ_t, i.e., $E_{t-1}(\epsilon_t {\epsilon'}_t) = D_t^{-1} H_t D_t^{-1} = R_t = \{\rho_{it}\}$. The conditional correlation estimator is given by:

$$\rho_{it} = \frac{\tau_{im,t}}{\sqrt{\tau_{ii,t}\tau_{mm,t}}} \tag{2.13}$$

where $\tau_{im,t}$ is assumed to follow a GARCH(1,1) process:

$$\tau_{im,t} = \overline{\rho}_{it} + a\left(\varepsilon_{m,t-1}\xi_{i,t-1} - \overline{\rho}_{it}\right) + b\left(\tau_{im,t-1} - \overline{\rho}_{it}\right) \tag{2.14}$$

where the term $\overline{\rho}_{it}$ is not the unconditional correlation between $\varepsilon_{m,t-1}$ and $\xi_{i,t-1}$[9]. Engle (2002) assumes that $\overline{\rho}_{it} \approx \tau_{im,t}$.

To ensure that H_t is positive definite and all elements in the conditional correlation matrix R_t are equal to or less than one (by definition), R_t is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{2.15}$$

where the correlation structure can be extended to the general DCC-GARCH model

$$Q_t = \overline{Q}_t \circ \left(ll^{'} - A - B\right) + A \circ \epsilon_{t-1}\epsilon_{t-1}^{'} + \mathrm{B} \circ Q_{t-1} \tag{2.16}$$

Where Q_t is a conditional symmetric positive definite variance-covariance matrix of ϵ_t; $\overline{Q}_t$ is the unconditional covariance matrix of ϵ_t, the vector of standardized residuals from the first stage estimation, i.e., $\overline{Q}_t = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t \epsilon'_t$; l is a vector of ones; A and B are symmetric parameter matrices; $\circ$ denotes the Hadamard product of an elementwise matrix multiplication procedure; Q_t^* is a matrix that takes the square roots of each element in Q_t. The model parameter set is estimated by QMLE and the second stage quasi-likelihood function is expressed as:

$$\mathrm{L}(\theta_2|\theta_1) = -\frac{1}{2}\sum_{t=1}^{T}(\ln(|R_t|) + \epsilon'_t R_t^{-1} \epsilon_t) \tag{2.17}$$

where θ_1 denotes all the unknown parameters in the first stage and θ_2 denotes the parameters to be estimated in the second stage. When Q_t is obtained, the conditional correlation matrix R_t

[9] The unconditional correlation between $\varepsilon_{m,t-1}$ and $\xi_{i,t-1}$ has no close form.

is then created by dividing the covariances in the Q_t matrix by the appropriate standard deviations in Q_t^* using equation (2.15) (Engle, 2002).

MES and CES estimation

In the second step, based on the conditional volatility and correlations obtained in the first step, we proceed to estimate the one-period-ahead MES and CES. The one-period-ahead MES and CES are expressed as[10]:

$$MES_{it}^{\alpha} = -\left[\sigma_{it}\rho_{it}\mathbb{E}_{t-1}\left(\varepsilon_{mt}\middle|\varepsilon_{mt} < \frac{VaR_{\alpha}}{\sigma_{mt}}\right) + \sigma_{it}\sqrt{1-\rho_{it}^{2}}\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < \frac{VaR_{\alpha}}{\sigma_{mt}})\right] \tag{2.18}$$

$$CES_{it}^{\alpha} = -w_{it}\left[\sigma_{it}\rho_{it}\mathbb{E}_{t-1}\left(\varepsilon_{mt}\middle|\varepsilon_{mt} < \frac{VaR_{\alpha}}{\sigma_{mt}}\right) + \sigma_{it}\sqrt{1-\rho_{it}^{2}}\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < \frac{VaR_{\alpha}}{\sigma_{mt}})\right] \tag{2.19}$$

where $\mathbb{E}(\cdot)$ is the tail expectation of the standardized innovations. In both specifications, the time-varying conditional correlation, ρ_{it}, completely capture the linear dependency between the market and each sector, while the second conditional expectation, $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < \frac{VaR_{\alpha}}{\sigma_{mt}})$, captures the remaining non-linear dependencies. The tail expectations on model innovations are then inferred based on GARCH-DCC residuals and conditional standard deviation/volatility. Besides volatility, correlations and tail expectations, CES further includes the fourth element, the sector's weight, w_{it}. It should be noted that the DCC model enables us to estimate merely correlations rather than causal relationship. MES and CES based on this method thus do not reflect causality but just tail dependency.

[10] Detailed proof from equations (2.3) to (2.18) and from (2.4) to (2.19) can be found in Banulescu and Dumitrescu (2015).

We use the non-parametric kernel estimation of the tail expectations $\mathbb{E}_{t-1}\left(\varepsilon_{mt}\middle|\varepsilon_{mt} < \frac{VaR_\alpha}{\sigma_{mt}}\right)$ and $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < \frac{VaR_\alpha}{\sigma_{mt}})$ based on Scaillet (2005), which is a non-parametric kernel estimation relying on the *i.i.d.* property of the innovations, following Banulescu and Dumitrescu (2015) and Brownlees and Engle (2012):

$$\widehat{\mathbb{E}}_{t-1}\left(\varepsilon_{mt}\middle|\varepsilon_{mt} < \frac{VaR_\alpha}{\sigma_{mt}}\right) = \frac{\sum_{t=1}^{T}\varepsilon_{mt}\Phi(\frac{VaR_\alpha/\sigma_{mt}-\varepsilon_{mt}}{h})}{\sum_{t=1}^{T}\Phi(\frac{VaR_\alpha/\sigma_{mt}-\varepsilon_{mt}}{h})} \tag{2.20}$$

$$\widehat{\mathbb{E}}_{t-1}\left(\xi_{it}\middle|\varepsilon_{mt} < \frac{VaR_\alpha}{\sigma_{mt}}\right) = \frac{\sum_{t=1}^{T}\xi_{it}\Phi(\frac{VaR_\alpha/\sigma_{mt}-\varepsilon_{mt}}{h})}{\sum_{t=1}^{T}\Phi(\frac{VaR_\alpha/\sigma_{mt}-\varepsilon_{mt}}{h})} \tag{2.21}$$

where VaR_α/σ_{mt} is the threshold, representing a systemic risk event; $\Phi(\cdot)$ denotes the normal c.d.f (Gaussian Kernel function), and h stands for the positive bandwidth parameter, which is set to be $T^{-1/5}$, where T is the sample size, based on the *i.i.d.* property of the innovations (Scaillet, 2005). After computing the tail expectations using equations (2.20) and (2.21), the MES and CES for sector *i* on day *t* can be obtained by equations (2.18) and (2.19), respectively.

CES% estimation

In the third step, daily CES% can be computed by equations (2.6) and (2.19).

2.4 Data

The dataset used in this study is the daily returns and market capitalization information of sectors in the Chinese stock market. The data are extracted from the Wind Financial Database for the period from 05 January 2009 to 24 August 2018. This study covers the 11 sectors in the

Chinese stock market, namely, Energy, Materials, Industrials, Consumer discretionary, Consumer staples, Health care, Financials, Information technology, Telecommunication services, Utilities, and Real estate, according to WIND classification. The definitions and descriptions are shown in Table 2.1. In terms of market capitalization, Figure 2.1 shows that the top three biggest sectors are sequentially Financials, Industrials and Materials, while Telecommunication Services has the smallest mean market capitalization during the sample period, followed by Utilities and then Real Estate.

Descriptive statistics of sectoral returns are given in Table 2.2. From the descriptive statistics, Information Technology sector has the highest average return and also the highest level of volatility, whereas the lowest mean return is seen in Energy sector. The lowest volatility is seen in Financials sector, and then in Consumer Staples and Utilities sectors. These findings correspond to the sentiment that the Chinese technology sector is relatively undiversified with small, emerging and growing technology companies. The rapid pace of technological innovation in this industry drives the quick development and evolution in this sector, signalling huge potentials and thus attracting speculative investors to take short-term horizon, making the overall returns in Information Technology more volatile than sectors composed of more mature companies such as banks, food and utilities companies, etc.

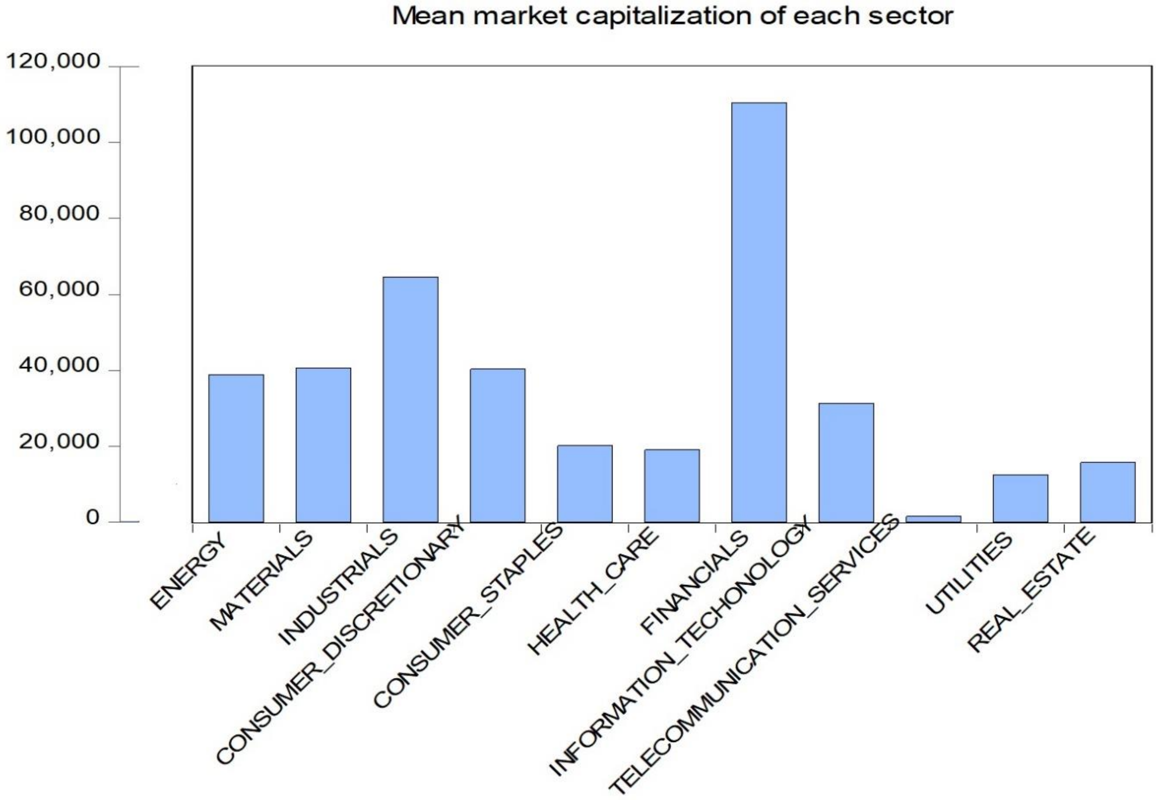


Figure 2.1 Mean market capitalization of each sector

Table 2.1 Sector classification and description

Sector	Description
ENERGY	Energy equipment, service, oil, gas and other fuels
MATERIALS	Chemicals, construction materials, containers and packaging, metal, mining and other materials
INDUSTRIALS	Aviation and defence, construction, electronics, infrastructure
CONSUMER_DISCRETIONARY	Car and parts, durable consumption, hotel, restaurants and others
CONSUMER_STAPLES	Food and beverage, and other retail products
HEALTH_CARE	Medical, health care, equipment and biotechnology
FINANCIALS	Banks, insurance, capital market, real estate
INFORMATION_TECHONOLOGY	Software, services, technological hardware
TELECOMMUNICATION_SERVICES	Telecommunication service and products
UTILITIES	Electricity, gas, water and other utilities
REAL_ESTATE	Real estate index

Note: Sectors are defined by the Wind Finance Database classification.

Table 2.2 Descriptive statistics of sectoral returns

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J.B.	ADF	Q(20)	Q^2(20)	ARCH(20)
ENERGY	0.022	8.437	-9.918	1.820	-0.420	7.250	1835.511***	-10.28***	59.05***	1526.2***	399.39***
MATERIALS	0.052	9.796	-9.684	1.956	-0.640	6.975	1705.720***	-10.88***	65.06***	3377.5***	643.63***
INDUSTRIALS	0.048	9.899	-9.783	1.854	-0.694	7.998	2631.134***	-10.72***	69.16***	3910.2***	677.19***
CONSUMER_DISCRETIONARY	0.069	9.894	-9.885	1.818	-0.664	7.550	2196.644***	-10.65***	68.25***	3380.2***	646.19***
CONSUMER_STAPLES	0.069	9.779	-9.705	1.666	-0.571	7.127	1793.079***	-10.70***	71.41***	2890.9***	587.02***
HEALTH_CARE	0.082	9.960	-9.817	1.785	-0.493	7.370	1962.286***	-10.77***	78.10***	3151.8***	617.16***
FINANCIALS	0.057	7.921	-9.461	1.639	-0.226	7.428	1937.186***	-9.46***	91.05***	939.84***	323.62***
INFORMATION_TECHONOLOGY	0.089	9.906	-9.929	2.163	-0.527	6.082	1037.301***	-10.86***	55.93***	4045.4***	649.86***
TELECOMMUNICATION_SERVICES	0.033	10.067	-10.039	2.074	-0.145	6.744	1379.058***	-10.13***	46.71***	1719.9***	414.65***
UTILITIES	0.037	9.912	-9.947	1.675	-0.667	10.259	5327.242***	-10.84***	92.69***	4586.7***	813.91***
REAL_ESTATE	0.060	9.864	-9.474	2.023	-0.440	6.101	1016.011***	-13.41***	40.99***	1421.3***	374.19***

Note: The table reports the descriptive statistics for the returns of the 11 sectors in the Chinese stock market at daily frequency from 5 January 2009 to 24 August 2018 (denominated in CNY). J.B. denotes Jarque-Bera statistics for the Jarque-Bera normality test. ADF denotes Augmented Dicky-Fuller test statistics for serial stationarity. Q(20) and Q^2(20) denote the Ljung-Box test statistics for autocorrelation in return and squared return series, respectively, taking 20 lags. ARCH(20) denotes the LM test statistics of the ARCH effects in the return series taking 20 lags. ***, **, and * refer to the 1%, 5% or 10% level of significance, respectively.

All sectoral returns are skewed to the left and have excessive kurtosis (higher than 3 as in a normal distribution), indicating fat-tails and excess peakedness at the mean and non-normal distributions. The leptokurtosis and non-normality of all series are also corroborated by statistically significant Jarque-Bera statistics at the 1% significance level. The ADF statistics significantly reject the null hypothesis of the presence of unit root in all sectoral series at the 1% significance level, indicating that all return series are stationary. The significant Q-statistics from the Ljung-Box test on returns and squared returns using 20 lags reject the null hypothesis of no serial correlation and indicate autocorrelation in all series. To test for the presence of ARCH effects in the residuals, the Engle (1982) test is computed for each series. The LM statistics for all series are significant, suggesting the presence of ARCH effects in all sectoral returns and thus corroborating the adoption of a GARCH-type model to estimate these series.

The choice of the sample period is justified for a couple of reasons. First, the 2008 global financial crisis period is explicitly excluded, as the profound impacts of the GFC might drive the volatility in the Chinese stock market and therefore generate biased results. Second, a few major IPOs prior to the Global Financial crisis, such as PetroChina Company Limited (PetroChina) and Industrial and Commercial Bank of China (ICBC)[11], may have caused structural changes in the weights of their affiliated sectors and the composition of the stock market, which could directly affect the CES results and make it difficult to clearly identify systemically important sectors without any compositional effect.

[11] PetroChina, China's biggest oil and gas producer, was listed in Shanghai in November 2007 (code: 601857) and became the largest listing in the world by market capitalization (5 November 2007, PetroChina becomes world's largest listed company, China Daily. Source: Xinhua). The Industrial and Commercial Bank of China (ICBC, code 601398), the largest bank in the world by market capitalization (Allen et al., 2014), had its dual IPOs in the Hong Kong and Shanghai Stock exchanges in 2006.

Notably, the sample period covers two major market crashes in the Chinese stock market that occurred during the post global financial crisis period. The first round of market crash started from August 2009, and the second from June 2015. While the first round marked the beginning of a subsequent long-lasting bear market, the second was even more severe with profound detrimental effects on the whole market. During the second-round crash, the market index dropped by more than 30% over 15 days and almost 45% within less than two months. The index value peaked to 5,178 points on 15 June, and plummeted to 3,585 in July and then 2850 on 26 August. Figures 2.2 and 2.3 show the clearly visible burst of market volatility in 2015. Likewise, the volatility of each sector also remarkably increased during this crashing period. Seen in Figures 2.2 and 2.3, volatility clustering is also obvious for each return series, which is consistent with the almost universal feature of asset return series in finance, which implies that information driving price changes arrives in brunches rather than being evenly spaced over time.

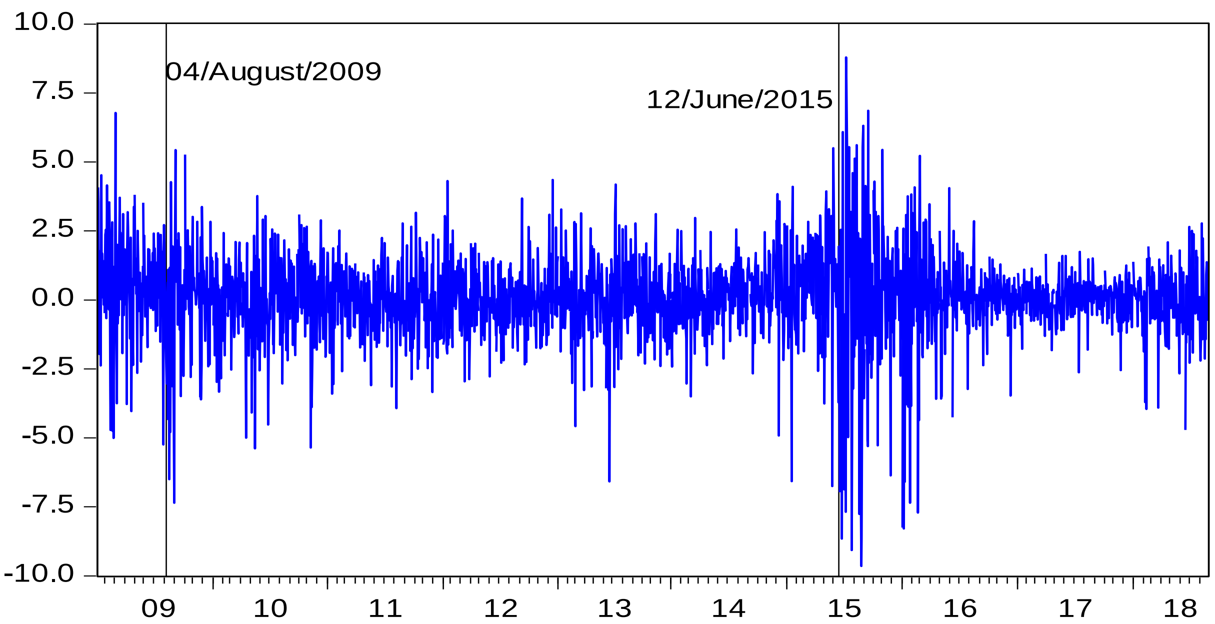


Figure 2.2 Market returns in China

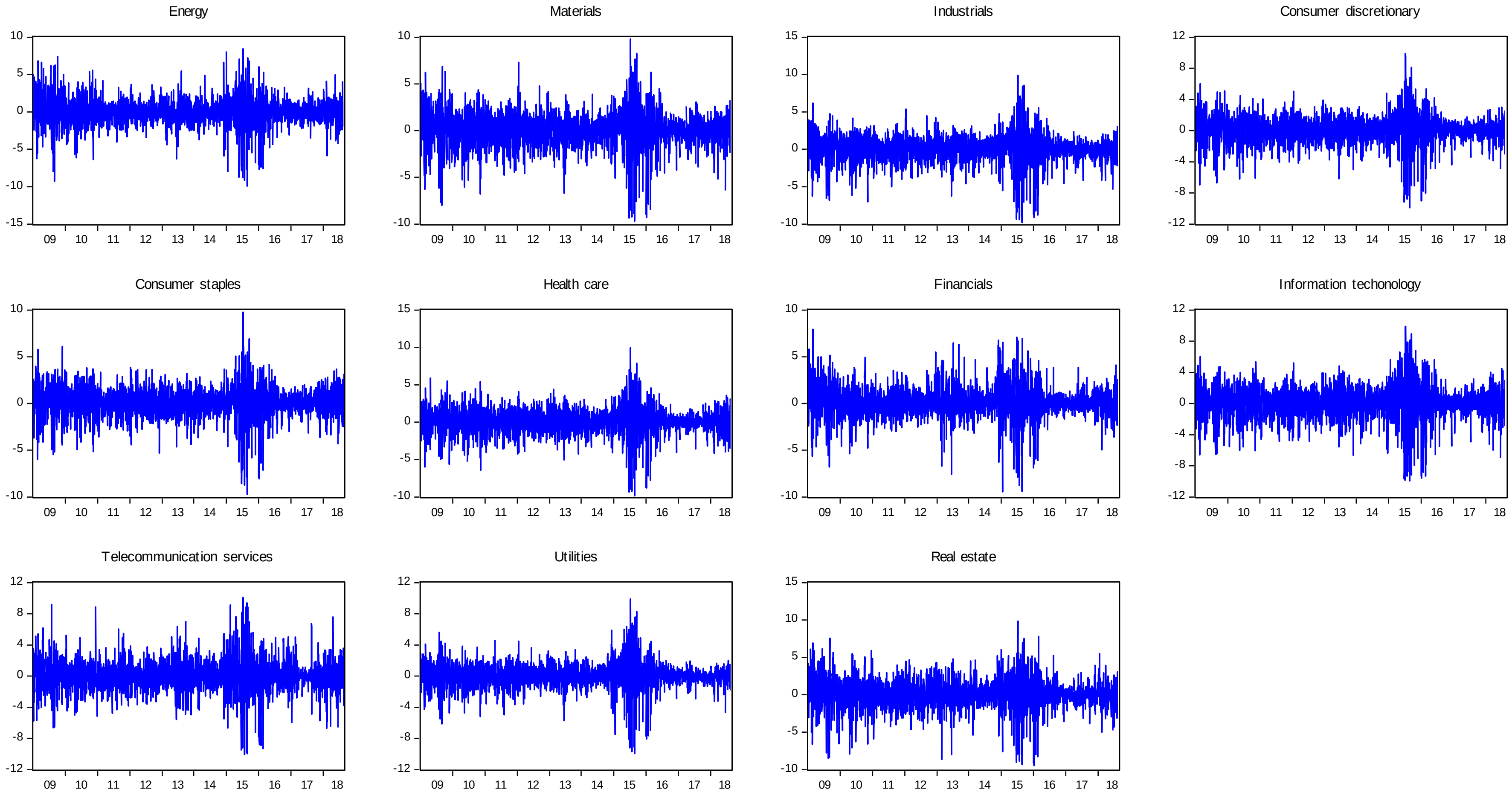


Figure 2.3 Sectoral returns in the Chinese stock market

2.5 Empirical results and discussion

2.5.1 Identifying SIS

In this study, a crisis is defined as a market distress exceeding the VaR(5%) as in Banulescu and Dumitrescu (2015). Using this 5% quantile, we derive a nonparametric measure of MES, and then calibrate CES and CES% by adding in the weight of individual sectors. Using the MES and CES of each sector, we then find the rankings of sectors' systemic importance. It is worth mentioning that similar results are obtained when using VaR(2%) as the systemic risk event, corresponding to a 2% market drop over a day, as used by Brownlees and Engle (2012)[12].

This study mainly seeks to identify the riskiest sector in the Chinese stock market by directly ranking them according to their MES and CES values. The main results are summarized in Table 2.3. Mean values of MES, CES (and CES %) of all sectors are reported in the table, calculated respectively over the full sample and two major crashing periods. Both crashing periods are set to be one month, respectively from 4 August 2009 to 4 September 2009, and from 12 June to 12 July 2015. The one-month window is assumed to make them comparable.

The MES results show that over the full sample and also the second crashing period, the top three contributors to the market loss are sequentially Information Technology, Materials and Industrials, while during the first crashing period, the top three are Materials, Energy and Real Estate. These results highlight the top systemic importance of Information Technology and its dominance in the second crashing period. Materials stands out as a top contributor to the market

[12] Results using VaR (2%) as the systemic crisis are available upon request.

loss in the first crashing period and ranks the second in both the whole sample period and the second crashing period, indicating that it is constantly among the riskiest sectors over the full sample. Industrials is another non-negligible driver of systemic loss, not only over the full sample, but also making notable contribution in the second crashing period. Energy and Real Estate are systemically important only in the first crashing period. In brief, among the three all-time systemically important sectors, only Materials is always a leading contributor in every stage of the sample period, while the other two, Industrials and Information Technology, are on average systemically important, but not playing a leading role in the first crashing period when Energy and Real Estate are ranked among the top instead.

The CES and CES (%) results deliver very different information than the MES results. Based on the CES ranking, Financials is identified as the most important sector, contributing the most to the market loss during the full sample and the first crashing period, and is ranked the second in the second crashing period. Industrials and Materials follow Financials to be the second the third most systemically important sectors over the full sample. Comparing the two crashing periods, Financials, Energy and Materials take the lead in the first crashing period, while Industrials, Financials and Consumer Discretionary are ranked the top during the second crash. CES (%) as the percentage version of CES, is computed only by CES and renders exactly the same rankings as CES. CES% results show that Financials as a dominant force in the system on average contributes 23.85% to the market’s overall loss, i.e., systemic risk. Industrials as the second most important sector for systemic risk makes an average contribution of 17.96%. These two sectors in turn take the leading role in two crashing periods, with Financials dominating the first crashing period (27.64%) while Industrials the second (21.03%).

Table 2.3 Estimated mean value of MES and CES

	MES			CES			CES(%)		
	Mean	Mean_C1	Mean_C2	Mean	Mean_C1	Mean_C2	Mean	Mean_C1	Mean_C2
ENERGY	3.228	6.105**	6.908	0.376	1.236**	0.528	11.127	23.921**	7.344
MATERIALS	3.817**	6.574***	8.349**	0.397*	0.753*	0.800	12.237*	14.622*	11.053
INDUSTRIALS	3.708*	5.447	8.252*	0.594**	0.736	1.505***	17.958**	14.267	21.039***
CONSUMER_DISCRETIONARY	3.546	4.773	7.754	0.339	0.268	0.871*	10.278	5.107	12.137*
CONSUMER_STAPLES	2.857	4.148	7.434	0.137	0.123	0.336	4.274	2.362	4.629
HEALTH_CARE	2.962	3.580	7.430	0.134	0.082	0.342	4.100	1.558	4.753
FINANCIALS	2.713	4.289	5.362	0.803***	1.440***	1.430**	23.846***	27.641***	19.615**
INFORMATION_TECHONOLOGY	4.017***	4.994	8.383***	0.283	0.119	0.788	8.841	2.267	11.068
TELECOMMUNICATION_SERVICES	3.018	4.709	6.864	0.012	0.029	0.025	0.372	0.563	0.335
UTILITIES	2.944	5.319	8.054	0.094	0.165	0.301	2.660	3.192	4.184
REAL_ESTATE	3.664	5.503*	7.180	0.144	0.234	0.274	4.308	4.501	3.842

Note: Mean_C1 refers to the mean values in the first crashing period, which is set to be one month from 04/08/2009 to 04/09/2009. Mean_C2 refers to the mean values in the second crashing period, which is set to be one month from 12/06/2015 to 12/07/2015. CES(%) is the percentage version of CES, which equals to $CES_{it}/\sum_i CES_{it}$. The highest value in each category is marked with ***, the second highest with **, and the third with *.

Comparing the results from MES and CES, the two systemic risk measures provide differed rankings of systemic importance of the sectors and identify different systemically important sectors (SIS). While MES analysis identifies Information Technology as the most systemically important sector over the full sample period and the second crash and Materials as the SIS in the first crashing period, CES results show that Financials takes the leading role over the full sample and in both crashing periods. Real Estate is ranked the third most important in the first crashing period only by MES but not by CES. In the second crashing period, Materials is identified as important by MES but not by CES, while for Consumer Discretionary it is the opposite. These results highlight the difference between MES and CES measures regarding which characteristics are considered to qualify the SIS.

It is not entirely surprising that MES analysis recognizes Information Technology as the all-time leading sector, as this sector has the highest volatility over the full sample period shown in Table 2.2. The average weight of this sector is, however, only 6.9%, making it among the smallest sectors in terms of market capitalization. Real Estate, another small sector whose average weight equals 3.9% but with high volatility, is recognized by the MES approach as among the top three in the first crashing period, but not considered important by CES results.

These seemingly counterintuitive results by the MES approach may imply that these results are mainly driven by volatility/interconnectedness, as the MES-based ranking highlights the systemic importance of some small sectors that are indeed highly volatile and possibly interconnected, but are unlikely to be the main force triggering market-wide crashes. The MES measure thus privileges the TITF logic while understating other potentially important factors, such as size. MES analysis therefore may not best suit our purpose of sectoral analysis. The

CES measure, on the other hand, addresses both the TITF and TBTF paradigms by including in weight, and renders more coherent rankings. The SIS identified by CES, Financials, contributes substantially to the stock market crashes in both crashing periods.

Both MES and CES results achieve the consensus that Industrials and Materials are among the top three systemically important sectors during the whole sample period, although with different rankings. Considering the crashing periods, both methods find systemic importance of Materials in the first crashing period, and of Industrials in the second crashing period. Similarly, Energy is simultaneously identified by both MES and CES as the second most important sector in and only in the first crashing period. The implication is that both methodologies, notwithstanding with different paradigms and emphases, commonly recognize the systemic importance of these three sectors over certain periods. These consistent findings are worth further probing into to find the underlying economic intuitions.

It is easier to understand and explain the above findings if linking them to the following facts. First, we try to explain the risk dominance of Financials, especially in the first crashing period starting from August 2009. This period corresponds to the aftermath of the 2008 global financial crisis. With increased market integration and cross-market correlations as a result of the GFC (Kim et al., 2015; Karanasos et al., 2016; Bala and Takimoto, 2017), shocks from the international market and their long lasting effects are still haunting China’s financial system, which is experiencing a slow recovery. Shown by extant empirical evidence, banks play a key role in risk transmission in the GFC and contribute the most to risk contagion from the US to other developed and emerging countries including China (Mollah et al., 2016). It is thus not surprising that the Chinese financial system, dominated by a banking sector (Allen et al., 2017), is found to be more influential than all the other sectors by the CES analysis, as it leads the risk and information flows in the market during this particular period. By contrast, Financials is no longer the most important sector in the second crashing period, implying the diminishing effect of the GFC on the Chinese stock market through its impacts on the Chinese financial system.

Considering the Industrials sector, its systemic importance over the full sample period and risk dominance during the second crashing period are recognized by both MES and CES methods. This can be clearly associated with the general trend of industrial growth in this country. Industrials has been a long-standing pillar industry of China's national economy since the beginning of the opening-up reform, and for long has contributed the most to the country's GDP, thus making it the most important and influential sector among all. Facing the surge of the service industry and other challenges, most notably the increasing energy and environmental constraints, however, the Industrials sector is susceptible to on-going adjustments and mounting uncertainties, leading to a continuous recession in this sector over the recent decade. When the growth slows down, uncertainties and risks build up. Our finding of the systemic importance of Industrials is in line with Wu et al. (2019), although the authors find that Industrials contributes the most to systemic risk, as it is recognized as a most central sector in the sectoral network constructed by a VAR-based approach, whereas we find it to be the second most important following Financials.

Similarly, both Wu et al. (2019) and this study find that Materials is among the riskiest sectors, irrespective of methods used in this study[13]. Empirical evidence shows that after the GFC,

[13] Another common finding is that Telecommunication Services contributes the least to the market loss based on our CES analysis, and Wu et al. (2019) find that this sector contributes and receives the least in terms of systemic risk contribution.

connectedness among commodity markets significantly rises (Zhang and Broadstock, 2018). The increased risk contribution of Materials in the first crashing period reflects the high level of risk in the international commodity market during the aftermath of the GFC that spills over to the domestic market, and induces more uncertainties and risks in this sector. In comparison, Wu et al. (2019) find Materials becoming more important between 2015 and 2017. Notwithstanding, the authors also attribute this change to the risk transmission from the global commodity market. The inconsistencies in the results between Wu et al. (2019) and this study can be attributed to the different paradigms of methods employed in two papers. While the VAR-based methodology used in Wu et al. (2019) measures mean dependence, MES and CES used in our study focus on extreme events and gauge tail dependency, which inevitably leads to different conclusions in terms of SISs.

Interestingly, Energy appears to be the second important sector in the first crashing period, with an average contribution of 23.92% in the one-month window, following Financials. Plausible explanations of Energy's temporary systemic importance are twofold based on the extant empirical evidence. First, dynamics in the international energy market such as large oil shocks can occasionally exert significant impacts on stock market risk (Zhang, 2017). After the 2008 global financial crisis, crude oil price remains at a low level, which causes great uncertainties to the Energy sector in the Chinese stock market. Second, financial markets exert increasing influences on energy markets (Creti and Nguyen, 2015). The high level of riskiness of the Energy sector during the first crashing period can thus be explained, at least partly, by the information originated from the financial system, i.e., Financials sector.

From the CES% results, it can be further noted that risk contribution tends to be very concentrated. During the whole sample period, 54.041% of the total loss in the market is attributed to the top three sectors in the ranking. This phenomenon is even more pronounced in the first crashing period, where the top three sectors contribute 66.184% of the total market loss. This trend continues to the second crashing period, where the top three sectors contribute to 52.791% of the market loss. This observation conveys very important implications for stock market regulators and supervisors. Imposing specific supervision and regulation on a small number of sectors with high risk concentration may help more efficiently and effectively bolster the market-wide stability.

2.5.2 Evolution of systemic risk

Figure 2.4 plots the evolution of short run percentage risk contributions (CES %) of three leading systemic sectors, namely, Financials, Industrials and Energy, over the sample period. Sectoral contributions to systemic risk from these sectors all show clear time-varying patterns. While Industrials constantly remains important (averagely around 20%) to the market systemic risk, Financials' contribution is more unstable, and its risk contribution has been substantially weakened especially since 2017. Energy plays but a temporary role in the market-wide systemic risk in 2009, when the global energy market faces substantial uncertainties. After that, its systemic contribution has been descending. In general, these results indicate that the major uncertainties causing the recent instabilities and risks in the China stock market are largely rooted in the problems and challenges of the country's manufacturing sector.

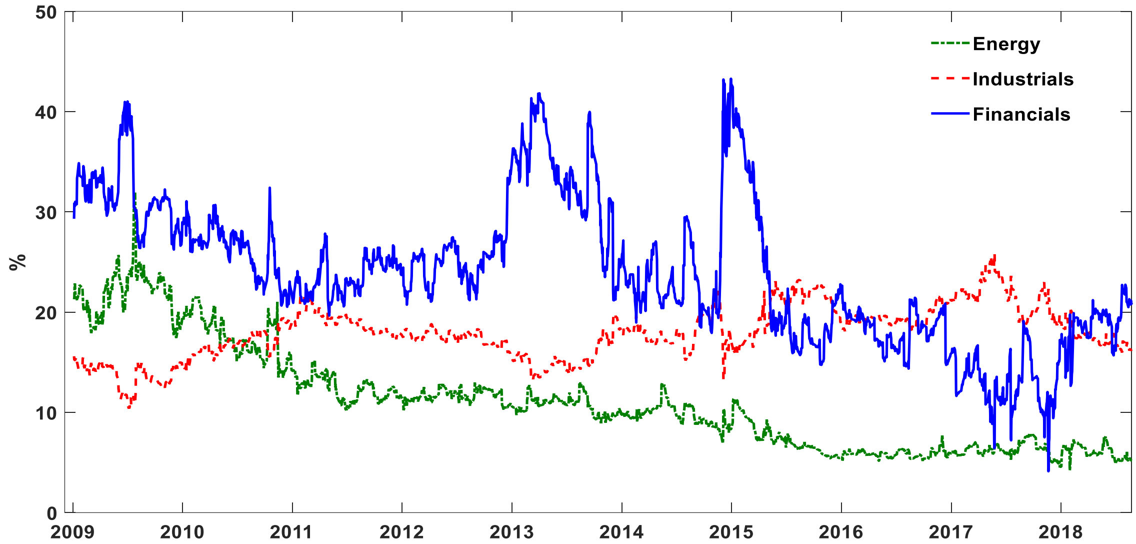


Figure 2.4 Percentage contribution (CES%) to systemic risk by three main sectors

Figure 2.5 plots the dynamics of both CES and MES for each of the three leading sectors over the sample period. The three sectors exhibit similar time trends. The overall evolutions of CES and MES for each sector are alike over the sample period, featured by lower levels of both measures during calm periods and sharp increases during the pre-crisis periods. As the crisis unfolds, the levels of both measures peak, and then decrease in the post-crisis periods. All sectors reach their maximum levels of CES and MES in the middle of 2015, exactly at the height of the second market crash. Interestingly, CES and MES show differences in detecting the increase in systemic influence. Taking Energy as an example, CES generally increases before MES. Also, as the second market crash unfolds, CES increases earlier than MES for all three sectors. This corroborates the argument that CES is able to identify the systemic characters earlier than MES. The explanation is that CES considers the increase of capitalization when the level of interconnectedness remains at the same level, thus enabling CES to identify the increase in systemic contribution before MES.

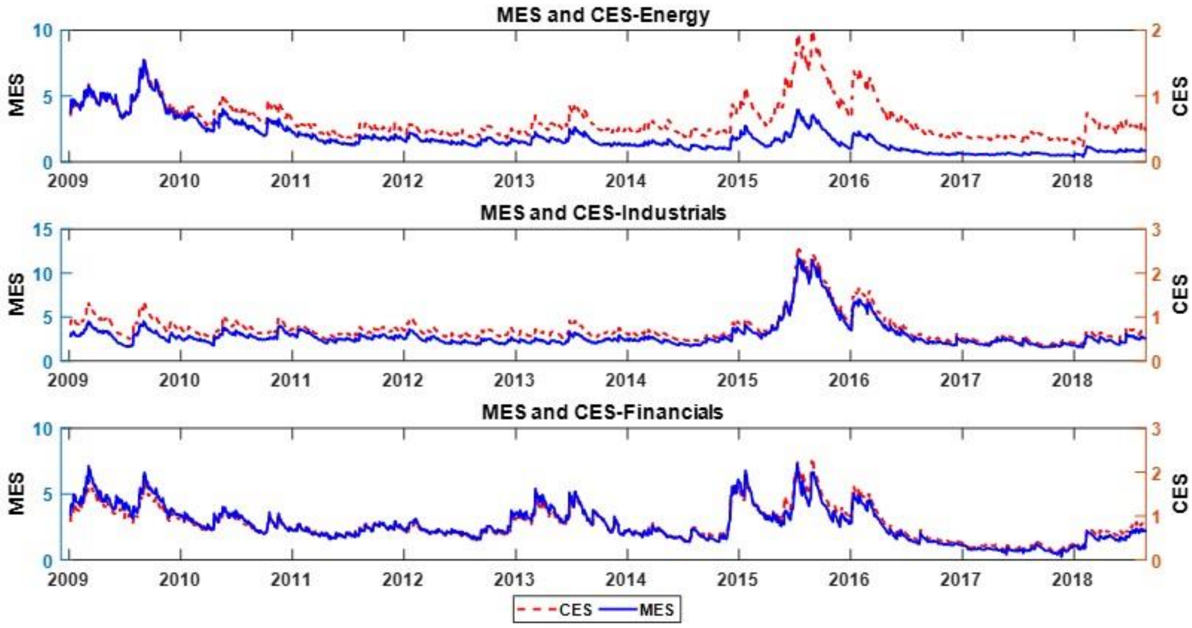


Figure 2.5 In-sample MES versus CES by three main sectors

2.6 Conclusions

Following the 2008 global financial crisis, it has been widely recognized that the failure or distress of some key individual financial institutions can generate negative externalities on the whole system and induce collapses of the market and harm the broader economy. There have been heated debates upon curbing systemic risk and its contagion among academics and regulators. This study follows the vine of literature of measuring the contribution of individual components to the systemic risk in the financial system.

Motivated by the literature focusing on measuring systemic risk and its potential contagion mechanisms, this study seeks to study the systemic importance of sectors in the Chinese stock market. Extending from a number of existing researches identifying systemically important financial institutions (SIFI) in the financial system, this study tries to approach this question from a sectoral perspective and identify the systemically important sectors (SIS) in the broader stock market. It is motivated by the conjecture that extreme movements of a particular sector may, similar to SIFIs, transmit information or risks across the stock market, therefore leading to system-wide volatility following its own. This study thus focuses on sectoral risk contributions to the system-wide systemic risk, to detect sectors' roles as important channels of information and risk transmission in the system. This role, however, has been neglected and sparsely studied in the literature. While financial institution's systemic risk contribution has been intensively explored, our endeavour to identify SISs in the stock market aims to provide an alternative perspective for analyzing systemic importance and risk transmission channels.

By looking at the systemic risk in the stock market, this study also addresses the significant importance of an efficient and stable stock market to long-run sustainable economic growth. Focusing on how risks spread across sectors in the stock market is an effective way to understand how systemic risk develops and evolves over time to affect the normal functioning of the stock market. Furthermore, our sample period covers a post-GFC period from 5 January 2009 to 24 August 2018, during which several severe market crashes hit China's stock market, causing detrimental effects on not only the market, its participants, but also the wider national economy. This study tries to identify the most important sectors not only during normal times but more importantly when extreme events occur, so as to send important messages to both investors and regulators for proactive risk management and regulating.

Methodologically, to estimate which sectors may influence the whole market to a greater extent, the stock market is viewed as a portfolio composed of its constituent sectors. Within the portfolio framework, we use a couple of most recently developed and parsimonious measures on modelling systemic risk, marginal expected shortfall (MES) and component expected shortfall (CES), to show how much each sector contributes to the overall systemic risk in China's stock market, based on publicly available market data. MES of a given sector is computed as the expected loss of the sector conditional on a systemic event, which is defined in this study as the decline of market returns equalling or worse than the level of its VaR (5%). CES, on the other hand, is a component approach encompassing both the standard MES and the weight of the sector, measured by the relative market capitalization of the sector. These two measures allow us to rank the sectors by estimating their riskiness based only on market data and identify the sectors that constitute a significant part of the total risk in the stock market. Compared to other prominent systemic risk measures in the portfolio framework, such as SRISK, the computation of MES and CES only needs daily market data, and is not bothered by the concern arising from assuming a constant leverage level even during turbulent periods. In contrast to the bottom-up portfolio approaches such as CoVaR assuming a single firm's distress, MES and CES reversely explore risk exposure of individual firms during system-wide distress, which should be a bigger concern intimidating market supervisors, regulators and investors.

Empirical results estimated by a DCC-GJR-GARCH (1,1) model and the time-varying MES, CES and CES (%) propose some important findings. The MES and CES approaches deliver very different information regarding which sector is the SIS in the market. First, Financials has been identified as the dominating force of systemic risk in the Chinese stock market during the entire sample period, using CES and CES% measures. Its extreme movements contribute the most to the overall market risk. The MES rankings, by contrast, show that Information Technology is the most important sector during the sample period. Considering the relatively small weight but high volatility of Information Technology, we argue that weights of sectors should matter. It matters especially when there are substantial differences in the weight of each sector. Simply using the MES measure may thus generate bias towards certain sectors with extreme movements, and the identified subjects may not necessarily be the most systemically important one in the system, but are some small, highly volatile or interconnected sectors which are unlikely to be a main driving force triggering market-wide crashes. The underlying explanation is that the MES measure privileges the TITF logic while understating other potentially important factors, such as size. The CES measure better suits our purpose of detecting sectoral importance, as it accounts for both the TITF and TBTF paradigms by including in weights and renders more coherent rankings.

The Industrials sector has been the foundation of the state economy and is recognized as a non-negligible force of systemic risk by both the MES and CES approaches. Its recent recession has become a most important source of stock market uncertainties and risks. Both methods also find systemic importance of Materials and Energy but only during the first crashing period. The implication is that both methodologies, notwithstanding their different paradigms and emphases, commonly recognize the systemic importance of these three sectors over certain periods. These findings are closely related to the domestic economic trends and international shocks, and prompt investors, regulators and policy makers to pay closer attentions to sectoral contribution to systemic risk, in order to proactively and timely adjust their strategies to achieve better risk management and regulatory designs.

In terms of the full-sample MES or CES, similar time trends are exhibited in the three leading sectors, Energy, Financials and Industrials. Specifically, the levels of both measures remain low during calm times, soar during pre-crisis periods, peak as the crisis unfolds, and decrease in the post-crisis periods. The mid-2015 witnesses the maximum levels of CES and MES of all sectors, corresponding to the second market crash period. Interestingly, CES increases earlier than MES for each leading sector when the crisis unfolds, indicating the advance of CES over MES in detecting the increase of systemic influence.

It is also worth noting that risk contribution tends to be concentrated based on the CES% results, as more than half of market loss is attributable to the sectors ranked as top three during the full sample period and both crashing periods. For stock market regulators and supervisors, those sectors should be the on the top of the regulation list. Gearing stringent prudential regulation towards a small number of sectors with high risk concentration may thus greatly improve the efficiency of improving the stock market governance and bolstering stock market stability.

Finally, the results from both methods clearly show that the most systemically important sectors in the Chinese stock market have been changing over time. Sectoral contributions to systemic risk show clear time-varying patterns, and the top three SISs identified for each crashing period are different, irrespective of method used. MES recognizes Materials, Energy and Real-Estate as the leading sectors in the first crashing period, and Information Technology, Materials and

Industrials in the second crashing period, while CES and CES (%) results rank Financials, Energy and Materials as the SISs in the first crashing period and Industrials, Financials and Consumer Discretionary in the second. For any savvy market participants or regulators, systemic importance of sectors thus should be evaluated from a dynamic rather than static perspective.

3 Identifying systemically important financial institutions in China: New evidence from a dynamic copula-CoVaR approach

This chapter examines risk spillovers in the Chinese financial system by adopting a time-varying copula-CoVaR approach. The analysis starts from identifying the systemically important financial institutions (SIFIs) for each industry group in China's Financials sector in a dynamic context. Then, by quantifying VaR, CoVaR and ΔCoVaR through time-varying copulas, strong evidence of upside and downside risk spillovers is found between the SIFIs and their affiliated industry groups, indicating risk interactions between SIFIs and the financial system. The empirical results further reveal the presence of asymmetric downside and upside risk spillover effects, indicating asymmetric hedging strategies for investors during market upturns and downturns. These findings provide useful implications to investors during risk management and asset allocation, and to authorities for the purposes of curbing systemic risk spillovers and sustaining financial stability.

3.1 Introduction

The distress and collapses of several key financial institutions can eventually lead to a massive systemic failure and impair the functioning of the whole financial system (Sedunov, 2016). This argument is evident when looking at the many corporate failures over the days or weeks after the collapses of several key institutions during the 2007-08 global financial crisis. Risks of big, complex and important institutions spread fast across firms, sectors and markets, leading to a broad recession and slow recovery in its aftermath, which could have resulted in the "*1930 style global financial and economic meltdown with catastrophic implications for production, income and jobs*" (Bernanke, 2009).

The severe adverse effects of the crisis incurred heavy social costs on rescuing the key institutions and preventing further system-wide collapse. Compared to *ex post* recovery and taxpayer bailouts, it is well realized that effective *ex ante* measures can greatly curb systemic risk before it builds up and propagates across the system, thus substantially reducing the negative externalities following a massive market meltdown. According to the Financial Stability Board (FSB, 2010), financial institutions whose disorderly failures contribute the most significantly to financial instability and wider economic disruption are identified as systemically important financial institutions (SIFIs). These institutions may only be a few, but due to their sizes, complexity and systemic interconnectedness (FSOC, 2011), their systemic influence is non-negligible (Billio et al., 2012). More intensive regulation and supervision imposed on these riskiest components in the financial network during normal times should therefore be at the heart of every effective regulatory framework (Acharya et al., 2012).

Since the G20 Pittsburgh Summit in September 2009, the too-big-to-fail (TBTF) problem associated with SIFIs has been central to many prominent regulatory frameworks. Subsequently, the Financial Stability Board (FSB) announced three measures to identify global SIFIs including size, market importance and interconnectedness. The financial institutions identified as G-SIFIs by these criteria are subject to more stringent regulation commensurate with their systemic importance. These tightened regulations include enhanced loss absorption capacity beyond the minimum of Basel III standards, higher recovery and resolution planning requirements, and strengthened supervision. The Basel Committee on Banking Supervision (BCBS) published in 2011 its indicator-based assessment approach of identifying G-SIBs, and a bucketing approach to categorize them accordingly, as well as additional regulatory requirements on G-SIBs (BCBS, 2011). Both the list of 29 G-SIFIs and the methodology and indicators will be reviewed regularly. These regulatory updates in the banking sector are followed by the insurance sector, marked by the publication of the G-SII list in 2013 by the International Association of Insurance Supervisors (IAIS) (IAIS, 2013) and an updated version in 2016 (IAIS, 2016).

Alongside with on-going policy updates, there has emerged a surge of academic research focusing on how to measure and score SIFIs. One stream of research employs balance sheet data to analyse the risk of individual banks in the financial market. By contrast, another main strand of literature relies on market available data to assess to what extent an individual bank contributes to the systemic risk, namely, their marginal risk contribution to systemic risk, and their exposure to systemic events. Using market data to gauge systemic risk has the advantages of data availability, higher data frequency, and the ability of real-time rather than lagged computation of the measures. Prominent examples of market data-based measures from a portfolio perspective are conditional value-at-risk (CoVaR) (Adrian and Brunnermeier, 2016), marginal expected shortfall (MES) (Acharya et al., 2017), component expected shortfall (CES) (Banulescu and Dumitrescu, 2015), SRISK (Brownlees and Engle, 2017), distressed insurance premium (DIP) (Huang et al., 2009, 2012), etc. Another group of market approach focuses on the network structure and interconnectedness among the components in the financial system, stressing the endogenous structural vulnerability of the system and assessing the systemic importance based on the interdependence among institutions. Seminal network models are, for example, Granger-causality network (Billio et al., 2012), variance decomposition-based network (Diebold and Yilmaz, 2014), and tail risk interdependence network (Hautsch et al., 2014).

This chapter seeks to explore systemic risk spillover effects in the Chinese financial system. We start from estimating marginal distributions of returns of financial institutions and their affiliated industry groups by an ARMA-GARCH specification, where the optimal lags are determined by the Akaike information criterion (AIC). We then use dynamic copulas to characterize the risk measures: value at risk (VaR), conditional value at risk (CoVaR) and delta conditional value at risk (ΔCoVaR) proposed by Adrian and Brunnermeier (2016). Financial institutions exhibiting the strongest spillover effects on their affiliated industry groups, as evidenced by the highest value of CoVaR, are identified as SIFIs in the financial system. The empirical evidence shows that Shanghai Pudong Development Bank (SPDB) is the SIFI in the Chinese banking industry, while Pacific Securities Co., Ltd. (PS) and Ping An Insurance (Group) Co. of China, Ltd. (PAI) are respectively identified as the SIFIs for Diversified Financials and

Insurance sectors. We then proceed to test the bidirectional upside and downside risk spillovers between these SIFIs and their corresponding industry groups using VaR, CoVaR and ΔCoVaR.

The contributions of this study are twofold. First, to the best of our knowledge, sparse studies in the extant literature have tried to explore systemic risk spillovers in the Chinese financial system using the CoVaR-copula approach. This approach tackles the issue of identifying the sources of and key contributors to systemic risk from a new perspective. It enables us to capture risk spillover patterns in a dynamic fashion. Based on CoVaR and ΔCoVaR computed by time-varying copulas, we manage to address possible time variation in the risk spillover pattern and identify the SIFI in this system by taking into account the evolution of market risks.

Second, our empirical findings show that there are strong bidirectional upside and downside risk spillovers between the SIFIs and their affiliated industrial groups, which demonstrate asymmetric and time-varying patterns. These findings offer policy implications to regulators for diagnosing systemic weaknesses and possible sources of risk spillover during both bullish and bearish periods, so as to enhance resilience of the whole system and promote financial market governance. Riding on the wave of its phenomenal economic growth, the financial system in China has been developing rapidly and experienced several reforms, especially its commercial banking system (Zhang and Wu, 2019). For stock market participants in the fast-evolving Chinese market, they should bear in mind systemic risk of both SIFIs and the sector/industry groups for effective risk management. The asymmetric upside and downside risk spillover effects within the financial system also imply that savvy investors could accordingly predict systemic risk and effectively adjust their hedging strategies and positions to protect portfolios from risk spillovers.

The remainder of the chapter is organized as follows. In Section 2, we review the relevant literature on risk spillovers within the Chinese financial system. In Section 3, we introduce the methodologies used in the empirical application. In Section 4, we present the data and discuss the empirical results. Section 5 summarizes the empirical results and concludes with policy and investment implications.

3.2 Literature review

The risk spillovers in financial markets of developed economies, such as European (Ghulam and Doering, 2018; Shahzad et al., 2019) and US (Billio et al., 2012) markets, have already drawn intense attention in the literature. Sparse studies, however, have made efforts on exploring the Chinese market, despite the critical role of the Chinese financial sector in fuelling the country's economic growth and its international importance to systemic risk and financial stability in the global market.

Among the existing literature focusing on measuring systemic risk and identifying the network structure in the Chinese financial system, the tail-event driven network approach (Hautsch et al., 2014; Härdle et al., 2016) is employed to calculate CoVaR and to explore the network topological characteristics (Wang et al., 2018a), as well as to identify tail risk interconnection among Chinese financial institutions (Fang et al., 2018a). The Diebold and Yilmaz (2014) method is employed to find evidence of strong interconnectedness in the commercial banking sector in China (Wang et al., 2018c). Gang and Qian (2015) measure systemic risk of financial institutions by Marginal Expected Shortfall (Acharya et al., 2017), while several others focus on China's banking sector (Fan et al., 2017; Huang et al., 2017; Xu et al., 2018) adopting MES, CoVaR, VI and SII as systemic risk measures.

In this study, we measure systemic risk and capture its spillover effects in the Chinese financial system by dynamic copula models. According to the theorem proved by Sklar (1959), a collection of marginal distributions can be "coupled" together by a *copula* to form a multivariate distribution, while from the opposite direction, any *n*-dimensional joint distribution function may be decomposed into its *n* marginal distributions. The dependence between these *n* variables can thus be fully described by a copula. Within the framework of copula, Patton (2006) is a pioneering study adopting time-varying copulas to study the dynamics of asymmetric dependence structure of exchange rates. Detailed reviews of the copula families can be found in Joe (1997), Nelsen (2006) and Patton (2012). With its strength in detecting dependence structure and its evolution, the copula approach has gained increasing popularity in empirical finance research (see for example, Reboredo and Ugolini, 2015; Liu et al., 2017; Mensi et al., 2017; Ji et al., 2018a; Ji et al., 2018b). An earlier comprehensive review of using copula methods in finance is found in Cherubini et al. (2004).

Within the framework of CoVaR, Mainik and Schaanning (2014) first propose to use copula to represent CoVaR. The extant literature has shown that the calculation of CoVaR can benefit from using copulas (Patton, 2006; Hakwa et al., 2015; Bernardi et al., 2017). While the usual correlation coefficient fails to capture the excess kurtosis and fat-tailedness when facing non-elliptical joint distribution, copula has its advances in capturing the non-normal characteristics of the joint distributions present in many common economic variables, and especially financial variables (Patton, 2006). By separately modelling marginal distribution and dependence, copula models render the flexibility to obtain different dependence measures with varied tail dependence features which linear correlation coefficients fail to capture, thus facilitating the computation of VaR and CoVaR. Furthermore, the various model specifications of time-varying copulas allow for time variation in the associated dependency parameters, making it possible to detect the dynamics of the market network structure.

While existing China-related studies quantify CoVaR by, for example, quantile regression (Fan et al., 2017), tail risk network (Wang et al., 2018a) or multivariate GARCH models (Huang et al., 2016; Huang et al., 2017), we use CoVaR and ΔCoVaR characterized and estimated by time-varying copulas to capture risk spillover patterns in the Chinese financial system. To the best of our knowledge, this CoVaR-copula approach has not been used in the existing literature to detect risk spillover effects in the Chinese financial system. Due to the advantages of copulas in measuring both average movements across marginal distributions and extreme upward and downward joint movements, the copula-CoVaR methodology enables us to flexibly and fully estimate both upside ad downside risk spillovers in the Chinese financial system.

3.3 Methodology

3.3.1 The marginal distribution model

Our starting point is to estimate marginal distributions of each return series in the full sample, which is characterized by an ARMA(p, q)-GARCH(m, n) specification:

$$r_{i,t} = \varphi_0 + \sum_{j=1}^{p} \varphi_j r_{i,t-j} + \varepsilon_{i,t} + \sum_{k=1}^{q} \theta_k \varepsilon_{i,t-k} \tag{3.1}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t} \tag{3.2}$$

where $r_{i,t}$ is the return of financial institution i at time t; φ_0 is a constant; p and q are the numbers of lags, which are non-negative integers; φ_j and θ_k are the autoregressive (AR) and moving average (MA) parameters, respectively; $z_t \sim i.i.d$; $\sigma_{i,t}^2$ is the conditional variance with its dynamics given by a GARCH model:

$$\sigma_{i,t}^2 = \omega_0 + \sum_{h=1}^{m} \alpha_h \varepsilon_{i,t-h}^2 + \sum_{k=1}^{n} \beta_k \sigma_{i,t-k}^2 \tag{3.3}$$

where ω_0 is a constant; n and m are the number of lags, which are non-negative integers; ε_{t-h}^2 and σ_{t-k}^2 are the ARCH and GARCH components, with α_h and β_k being the parameters, respectively. The numbers of lags (p, q, m and n) are decided by the Akaike information criteria.

Considering the non-normality characteristics of the GARCH model residuals (Engle and Gonzalez-Rivera, 1991; Nelson, 1991; Bollerslev and Wooldridge, 1992), and possible time-varying parameters of the error distribution, we build our univariate margin model based on Hansen's skewed Student-*t* distribution (Hansen, 1994) to allow for a control of asymmetry and fat-tailedness of return series and to obtain time-varying higher moments (Reboredo et al., 2016; Liu et al., 2017). Hansen's model is specified as:

$$f(z_{i,t}; \upsilon, \eta) = \begin{cases} bc\left(1 + \frac{1}{\upsilon-2}\left(\frac{bz_{i,t}+a}{1-\eta}\right)^2\right)^{-(\upsilon+1)/2} & \text{if } z_{i,t} < -a/b \\ bc\left(1 + \frac{1}{\upsilon-2}\left(\frac{bz_{i,t}+a}{1+\eta}\right)^2\right)^{-(\upsilon+1)/2} & \text{if } z_{i,t} \geq -a/b \end{cases} \tag{3.4}$$

where $f(z_{i,t};\upsilon,\eta)$ is the density function for the random variable Z; υ is the degree-of-freedom parameter; η is the symmetric parameter; the intervals for the distribution parameters are $2 < \upsilon < \infty$, $-1 < \eta < 1$; a, b and c are defined as $a \equiv 4\eta c\left(\frac{\upsilon-2}{\upsilon-1}\right)$, $b^2 \equiv 1 + 3\eta^2 - a^2$, and $c \equiv \Gamma\left(\frac{\upsilon+1}{2}\right)/\sqrt{\pi(\upsilon-2)}\Gamma\left(\frac{\upsilon}{2}\right)$, respectively.

3.3.2 Time-varying copula models

The dependence structure in the financial market evolves and exhibits non-linear and asymmetric patterns (Chao et al., 2015). Co-movements among market components driven by the time-varying network structure thus tend to change over time, which should be a critical concern of any regulatory regime (Ji et al., 2018b). To address the non-linear, asymmetric and dynamic characteristics of the market dependence structure, we employ the time-varying copula models to characterize and compute the risk measures, based on its advantages in detecting non-linear asymmetric tail dependence while allowing for time-variation in parameters to address time-varying dependence structure (Patton, 2006; Mensi et al., 2017).

In the family of copulas, there are diverse specifications capable of capturing complex patterns of dependence in tails. Among the well-known and widely adopted bivariate copula models, the tail dependence parameter for the Gaussian copula is zero, indicating no tail dependence between the variables. Both the Clayton and Gumbel copulas and their rotated versions display asymmetric tail dependence. Clayton captures lower tail dependence and upper tail independence, while Gumbel captures upper tail dependence and lower tail independence, with their rotated versions capturing the opposite to their own. The Symmetrized Joe-Clayton (SJC) copula captures differing upper and lower tail dependence. The Student-t copula captures symmetric tail dependence.

Let $C(u,v)$ denote the basic form of static copula[14], and let $\mathrm{F_X}(x)$ and $\mathrm{F_Y}(y)$ denote the continuous marginal distributions of random variables *x* and *y*, respectively. The bivariate joint cumulative distribution function (*c.d.f.*) of *x* and *y* is decomposed as:

$$\mathrm{F_{XY}}(x,y) = C(u,v) = C\big(\mathrm{F_X}(x), \mathrm{F_Y}(y)\big) \tag{3.5}$$

where the copula function $C(u,v)$ couples together the marginal distributions of *x* and *y* and form a bivariate joint distribution of *x* and *y*, $\mathrm{F_{XY}}(x,y)$. The bivariate joint probability density function (*p.d.f.*) of *x* and *y*, $f_{\mathrm{XY}}(x,y)$, is decomposed as:

$$f_{\mathrm{XY}}(x,y) = c(u,v) f_{\mathrm{X}}(x) f_Y(y) \tag{3.6}$$

where $c(u,v) = \partial^2 C(u,v)/\partial u \partial v$; $f_{\mathrm{X}}(x)$ and $f_Y(y)$ are the marginal probability density functions for *x* and *y*, respectively. In general, copula theory can be used to link together univariate margins to form a multivariate joint distribution function, or from the opposite direction, to decompose an *n*-dimensional multivariate joint distribution into *n* univariate marginal distributions and a dependence function, namely, an *n*-dimensional copula (Sklar, 1959; Patton, 2012). Using copula models, we are enabled to characterize the joint distributions of return series and quantify their tail dependence.

[14] Joe (1997), Nelsen (2006) and Patton (2012) provide detailed reviews of copulas.

While static copulas measure time-invariant dependence among variables of interests, time-varying copulas allow for evolution in parameters and therefore address time-varying patterns in dependence. Drawn on Patton (2006, 2012), Mensi et al. (2017), Liu et al. (2017) and Ji et al. (2018a), we construct seven time-varying copula models in this study, derived from their static counterparts using specific evolution equations to allow the model parameters to evolve over time while keeping the functional form fixed during the sample period[15]. The seven copula specifications are time-varying Gaussian, Clayton, Rotated Clayton, Gumbel, Rotated Gumbel, SJC and Student-t copulas. To estimate the copula model parameters, we adopt maximum likelihood, while the most fitting copula is selected by minimizing the AIC value. Following Patton (2006) and Liu et al. (2017), the evolution equations for the dependence parameters in each copula are specified as follows.

For the Gaussian and Student-t copulas, the evolution of the dependence parameter ρ_t is assumed to follow an ARMA (1, q)-type process:

$$\rho_t = \Lambda\left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q} \sum_{j=1}^{q} \Phi^{-1}\left(u_{t-j}\right) \cdot \Phi^{-1}\left(v_{t-j}\right)\right) \tag{3.7}$$

where $\Lambda(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$ is the modified logistic transformation that retains ρ_t in $(-1,1)$; $\Phi^{-1}(x)$ is the normal distribution quantile function. The dependence parameter ρ_t is explained by the constant ψ_0, the autoregressive term parameter ψ_1, and the parameter of the average of the last q observations of the transformed variables, ψ_2. For the Student-t copula, the dynamics for ρ_t is characterized by the same specification, only that $\Phi^{-1}(x)$ is substituted

[15] The regime switching copula model allows for a time-variant functional form of copula (Rodriguez, 2007), but this alternative approach is not discussed here in order to keep the focus of this study.

by $t_n^{-1}(x)$, which is the quantile function of the univariate Student-t distribution with the degree-of-freedom *n*.

The evolution of the dependence parameters of Clayton, Gumbel and their rotated versions is also assumed to follow an ARMA (1, q)-type process:

$$\delta_t = \Lambda\left(\omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right) \tag{3.8}$$

where for time-varying Clayton and Rotated Clayton, $\Lambda(x) = x^2$ to retain δ_t in $(0, +\infty)$; for time-varying Gumbel and Rotated Gumbel, $\Lambda(x) = 1 + x^2$ so that δ_t is kept in $(1, +\infty)$.

For the SJC copula, the evolution of the two dependence parameters is assumed to follow:

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U\tau_{t-1}^U + \alpha_U\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right) \tag{3.9}$$

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L\tau_{t-1}^L + \alpha_L\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right) \tag{3.10}$$

where $\Lambda(x) = (1 + e^{-x})^{-1}$ is the logistic transformation to retain τ_t^U and τ_t^L in $(0,1)$.

3.3.3 Risk spillovers and CoVaR

To investigate risk spillovers in the Chinese financial system, we adopt three risk measures: value at risk (VaR), conditional value at risk (CoVaR), and delta conditional value at risk (ΔCoVaR), which are to be characterized and computed by copulas. The standard firm-level risk measure VaR quantifies the maximum possible loss of a given portfolio within a set time horizon at a given confidence level, assuming normal market conditions and no trading in the portfolio. It reveals the possibility of the biggest loss without the presence of any tail events, and is often used to gauge how much capital is needed to cover possible loss (Philippe, 2001). The given significance level α indicates that the probability of a loss greater than the VaR is less than or equal to α. The downside $VaR_{i,t}^{\alpha}$ and upside $VaR_{i,t}^{1-\alpha}$ for returns of institution *i* at time *t* are defined as:

$$P\left(r_{i,t} \leq VaR_{i,t}^{\alpha}\right) = P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha \tag{3.11}$$

Further, the downside and upside VaRs are computed as:

$$VaR_{i,t}^{\alpha} = \mu_{i,t} + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_{i,t} \tag{3.12}$$

$$VaR_{i,t}^{1-\alpha} = \mu_{i,t} + t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_{i,t} \tag{3.13}$$

where $\mu_{i,t}$ and $\sigma_{i,t}$ are the conditional mean and standard deviation of returns, computed based on results from equations (3.1) and (3.3), respectively; $t_{\upsilon,\eta}^{-1}(\alpha)$ and $t_{\upsilon,\eta}^{-1}(1-\alpha)$ are α and $1-\alpha$ quantiles of a skewed-*t* distribution in equation (3.4).

While VaR measures a single asset/firm's risk in isolation, the CoVaR measure considers losses of total assets/all firms. Drawn from the definition of CoVaR in Adrian and Brunnermeier (2016) and generalized by Girardi and Ergün (2013), the conditional value-at-risk (CoVaR) of a financial institution *i* relative to another financial institution *j* is defined as the VaR of *j*, conditional on *i* being in distress as measured by its VaR (namely, when *i*'s return is less than the α-quatile). It therefore captures how risk in the particular institution *i* can spill over to institution *j* and affect *j*'s risk level, indicating *i*'s risk impacts on any given institution in this system.

More generally, when CoVaR adopts a conditional change in VaR of the financial system and estimates the potential financial system losses conditional on the extreme movement of a particular financial institution, it quantifies the marginal risk contribution of the individual institution to the wider system, and vice versa. The CoVaR approach takes into account the interconnectedness and interaction effects in the financial system that may contribute to the building-up and amplification of systemic risk, thus having been largely employed in empirical studies. Considering the focus of this study, CoVaR is an informative tool to serve our purpose.

Denote the VaR of institution j as $CoVaR_{j,t}^{\beta}$, conditional on institution *i*'s return being lower than the α quantile $VaR_{i,t}^{\alpha}$ (downside risk), or as $CoVaR_{j,t}^{1-\beta}$ when *i*'s return is higher than the $1-\alpha$ quantile $VaR_{i,t}^{1-\alpha}$ (upside risk). The downside $CoVaR_{j,t}^{\beta}$ and upside $CoVaR_{j,t}^{1-\beta}$ are defined by the β quantile of the conditional probability distribution of $r_{j,t}$:

$$P\left(r_{j,t} \leq CoVaR_{j,t}^{\beta} | r_{i,t} \leq VaR_{i,t}^{\alpha}\right) = P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta} | r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \beta \qquad (3.14)$$

Computing CoVaR thus requires determination of the quantile of a conditional distribution. Equation (3.14) can be expressed as an unconditional bivariate distribution:

$$\frac{P\left(r_{j,t} \leq CoVaR_{j,t}^{\beta}, r_{i,t} \leq VaR_{i,t}^{\alpha}\right)}{P\left(r_{i,t} \leq VaR_{i,t}^{\alpha}\right)} = \frac{P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta}, r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right)}{P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right)} = \beta \qquad (3.15)$$

Given by equation (3.11) that $P\left(r_{i,t} \leq VaR_{i,t}^{\alpha}\right) = P\left(r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha$, equation (3.15) is transformed to:

$$P\left(r_{j,t} \leq CoVaR_{j,t}^{\beta}, r_{i,t} \leq VaR_{i,t}^{\alpha}\right) = P\left(r_{j,t} \geq CoVaR_{j,t}^{1-\beta}, r_{i,t} \geq VaR_{i,t}^{1-\alpha}\right) = \alpha\beta \quad (3.16)$$

In this study we follow Reboredo and Ugolini (2015) and several others to compute CoVaR by copulas. The joint probability in equation (3.16) can then be rewritten as:

$$\mathrm{C}\left(F_{r_{j,t}}\left(CoVaR_{j,t}^{\beta}\right), F_{r_{i,t}}\left(VaR_{i,t}^{\alpha}\right)\right) = \alpha\beta \quad (3.17)$$

$$\mathrm{C}\left(F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right), F_{r_{i,t}}\left(VaR_{i,t}^{1-\alpha}\right)\right) - F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right) - F_{r_{i,t}}\left(VaR_{i,t}^{1-\alpha}\right) + 1 = \alpha\beta \quad (3.18)$$

where $CoVaR_{j,t}^{\beta}$ and $CoVaR_{j,t}^{1-\beta}$ denote the downside and upside CoVaRs; $F_{r_{j,t}}$ and $F_{r_{i,t}}$ are the marginal distribution functions of returns of institutions *i* and *j*. Using a two-step approach in Reboredo and Ugolini (2015) and Reboredo et al. (2016), we first calculate the value of $F_{r_{j,t}}\left(CoVaR_{j,t}^{1-\beta}\right)$ by solving equations (3.17) and (3.18), based on the given significance levels α and β and the selected copula function form. Then by computing $F^{-1}\left(F_{r_{j,t}}\right)$, the values of downside and upside CoVaRs can be obtained.

Based on the concept of CoVaR, Adrian and Brunnermeier (2016) define ΔCoVaR to estimate the risk component in institution *j* that commoves with the risk of institution *i*. In other words, ΔCoVaR captures the part of systemic risk in institution *j* that can be attributed to institution *i*'s risk, and can thus measure tail-dependence between the two institutions. It is calculated as the change in CoVaR of j, conditional on i's return shifting from its median state (i.e., 50% quantile with $\alpha = 0.5$) to a distressed state (i.e., adverse $VaR^{\alpha}_{i,t}$):

$$\Delta CoVaR^{\beta}_{j|i,t} = \frac{\left(CoVaR^{\beta}_{j|i,t} - CoVaR^{\beta|\alpha=0.5}_{j|i,t}\right)}{CoVaR^{\beta|\alpha=0.5}_{j|i,t}} \tag{3.19}$$

In equations (3.15)-(3.19), *i* and *j* can be generalized from representing an individual institution to representing an industry group or the whole financial sector, equivalent to a portfolio composed of all financial institutions in that group or sector. The marginal risk contribution of *i* to *j* measured by CoVaR and ΔCoVaR can then be generalized to capture marginal risk contribution of a particular institution, such as SIFI, to an industry group or the whole financial system, and vice versa.

3.4 Empirical results

3.4.1 Sample analysis

The dataset employed in our empirical study is collected from the WIND financial database. It consists of daily returns of 22 publicly traded financial institutions from 02 January 2008 to 20 August 2018. The financial institutions in our sample are categorized into three financial industry groups based on the four-level industrial structure defined by WIND. These industry groups are Banks, Diversified financials, and Insurance Ⅱ, with each group's index provided by WIND to represent group-level returns. All three industry groups belong to the Financials sector. Table 3.1 lists the trading codes, full names and abbreviations of the 22 financial institutions and three industry groups within the financial system in China.

Table 3.1 Sample description

Panel A: Banks		
000001	Ping An Bank Co Ltd.	PAB
002142	Bank of Ningbo	BNB
600000	Shanghai Pudong Development Bank	SPDB
600015	Hua Xia Bank co., Limited	HXB
600016	China Minsheng Banking Corporation	CMBC
600036	China Merchants Bank Co Ltd.	CMB
601009	Bank of Nanjing	BNJ
601166	Industrial Bank Co Ltd.	IBC
601169	Bank of Beijing Co Ltd.	BB
601328	Bank of Communications Co. Ltd.	BCM
601398	Industrial & Commercial Bank of China (The) – ICBC	ICBC
601939	China Construction Bank Corporation Joint Stock Company	CCB
601988	Bank of China Limited	CB
601998	China CITIC Bank Corporation Limited	CITIB
Panel B: Diversified Financials		
600030	CITIC Securities Company Limited	CITIS
601099	The Pacific Securities Co., Ltd.	PS
000563	Shaanxi International Trust Co., Ltd.	SIT
600643	Shanghai AJ Group Co., Ltd.	SAJ
600816	Anshan Trust & Investment Co., Ltd.	ATI
Panel C: Insurers		
601318	Ping An Insurance (Group) Co. of China, Ltd.	PAI
601601	China Pacific Insurance (Group) Co., Ltd.	CPI
601628	China Life Insurance (Group) Co., Ltd.	CLI
Panel D: Index		
882115	Banks Industry Group Index	Banks
882116	Diversified Financials Industry Group Index	Diversified Financials
882117	Insurance Industry Group Index	Insurance

Notes: The table reports the basic information including trading codes, full names and abbreviations of the 22 financial institutions and the three industry groups (Banks, Diversified Financials, and Insurance) as defined by the WIND database in our sample.

Prior to 2008, many financial institutions in China had not been listed, including several important ones such as China Construction Bank, China CITIC Bank, Industrial Bank, Bank of Beijing, Bank of Nanjing, and Bank of Ningbo. Considering the complexity and importance of these financial institutions, our sample period starts from the beginning of 2008.

In addition, our sample period covers a period of over ten years. Several systemic events inflicting stock market turbulence and crashes in the recent decade are covered by this time span, including the 2008 global financial crisis and its aftermath, the stock market crash in August 2009 preluding a long-lasting bearish market, the credit crunch in the banking sector in June 2013, the 2015 stock market turbulence starting from June 2015 and lasting until early 2016, etc.

Table 3.2 reports the descriptive statistics of the returns of each individual financial institution and indices of the industry groups. Seen in the table, mean returns for all series are positive during the sample period, except the Pacific Securities Co., Ltd. (PS) and China Life Insurance Co., Ltd. (CLI). Anshan Trust and Investment Co., Ltd. (ATI) has the highest mean return among all. All series appear to be leptokurtic with kurtosis exceeding three as in a normal distribution, indicating excess kurtosis and fat tails in all series. The non-normality features are further corroborated by the Jarque-Bera statistics which significantly reject the null hypothesis of normality at the 1% significance level for all return series, thus validating our choice of the Hansen's model for specifying marginal distributions. Moreover, the ADF test significantly rejects the null hypothesis of presence of unit root at the 1% significance level, indicating stationarity of all return series. The Ljung-Box statistics rejects the null hypothesis of no serial correlations in returns and squared returns at the 1% significance level. The ARCH effect test results significantly reject the null hypothesis of no ARCH effects in the return series at the 1% significance level.

Table 3.2 Descriptive statistics of return series

	Mean	Max	Min	Std dev	Skewness	Kurtosis	Jarque-Bera	ADF	Q(20)	$Q^2(20)$	ARCH(20)
PAB	0.027	10.042	-10.020	2.459	0.262	6.650	1466.563***	-49.944***	31.107*	880.502***	281.758***
BNB	0.043	10.073	-10.016	2.418	0.129	6.217	1123.835***	-52.741***	53.126***	604.539***	224.796***
SPDB	0.031	10.031	-10.026	2.313	0.244	7.471	2181.838***	-50.452***	37.016*	1483.962***	373.390***
HXB	0.026	10.070	-10.048	2.344	0.091	6.807	1567.191***	-51.789***	32.604**	1444.314***	371.781***
CMBC	0.028	10.101	-10.000	2.116	0.312	7.663	2387.826***	-50.150***	45.161***	998.211***	305.603***
CMB	0.036	10.026	-10.007	2.203	0.242	7.066	1808.232***	-50.540***	35.759**	1388.630***	379.127***
BNJ	0.050	10.065	-10.013	2.278	0.157	6.996	1733.566***	-51.594***	42.919***	936.896***	357.271***
IBC	0.033	10.053	-10.020	2.376	0.181	6.810	1579.656***	-49.951***	43.428***	1267.930***	338.191***
BB	0.020	10.054	-10.013	2.166	0.245	7.560	2269.061***	-53.552***	37.711***	977.550***	340.305***
BCM	0.002	10.103	-10.058	2.019	0.178	9.285	4274.266***	-48.990***	65.222***	1470.091***	447.457***
ICBC	0.018	10.053	-10.043	1.635	0.080	10.606	6242.737***	-49.704***	61.514***	921.439***	346.156***
CCB	0.022	10.039	-10.094	1.815	0.234	9.339	4358.556***	-50.067***	62.502***	1535.334***	473.934***
CB	0.010	10.164	-10.040	1.655	0.582	11.660	8236.389***	-50.614***	48.616***	1363.682***	422.346***
CITIB	0.018	10.090	-10.025	2.300	0.357	7.189	1947.863***	-50.690***	42.459***	816.881***	271.675***
CITIS	0.024	10.043	-10.016	2.804	0.155	5.801	856.420***	-48.667***	38.860***	1263.549***	359.239***
PS	-0.025	10.095	-10.030	3.039	0.038	5.560	707.798***	-51.292***	40.089***	2557.895***	551.242***
SIT	0.033	10.061	-10.043	3.219	-0.033	5.074	464.282***	-51.272***	21.091	908.349***	274.993***
SAJ	0.036	10.066	-10.030	3.005	0.130	5.670	776.534***	-49.095***	37.306**	1338.829***	371.140***
ATI	0.063	10.044	-10.024	3.057	0.115	5.668	773.755***	-49.927***	41.074***	1291.298***	348.047***
PAI	0.038	10.017	-10.004	2.412	0.045	6.097	1035.631***	-50.134***	43.637***	1110.339***	344.566***
CPI	0.025	10.033	-10.007	2.512	0.139	5.215	537.367***	-50.757***	50.212***	735.439***	260.102***
CLI	-0.001	10.036	-10.007	2.429	0.382	6.296	1234.945***	-50.278***	63.398***	1394.995***	386.973***
Banks	0.019	10.021	-9.971	1.858	0.136	8.418	3174.747***	-51.019***	53.064***	1582.417***	407.219***
Diversified Financials	0.009	10.026	-10.000	2.683	0.062	5.708	792.995***	-49.261***	36.583**	1681.263***	420.265***
Insurance	0.025	10.014	-10.000	2.317	0.115	5.961	951.549***	-50.749***	57.967***	1200.778***	362.142***

Notes: The table reports the descriptive statistics for the returns of the 22 financial institutions and three industry group indices at daily frequency from 2 January 2008 to 20 August 2018 (denominated in CNY). Jarque-Bera denotes the Jarque-Bera test statistics for normality. ADF denotes the statistics of the augmented Dicky-Fuller test. Q(20) and $Q^2(20)$ denote the statistics of the Ljung-Box test for autocorrelation in returns and squared returns, respectively (with 20 lags). ARCH(20) are the ARCH effect test statistics with lag=20. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% or 10% levels, respectively.

3.4.2 Marginal model results

The results of marginal model estimates are reported in Table 3.3, using equations (3.1)-(3.3). The lag values of p and q are considered ranging from zero to a maximum of three, while m and n from zero to a maximum of two. These lag values are then selected so as to minimize the AIC values. The return series tend to have different best ARMA fits, and the selections of p and q vary across series. For example, ARMA (1,1) is the best fitting model for Bank of Ningbo (BNB), while ARMA (1, 3) is the best fit for Shanghai Pudong Development Bank (SPDB). For the GARCH model specification, m and n are selected as one, with GARCH (1,1) being the optimal model for all series.

Several goodness-of-fit tests are conducted and the results are reported in the last few columns in Table 3.3. Marginal distributions for most return series exhibit asymmetry, evidenced by the significantly positive symmetry parameter λ at the 5% significance level, except for PS and SIT.

The Ljung–Box and Engle's LM test statistics cannot reject the null hypotheses of no serial correlation or ARCH effects in the standardized residuals and squared standardized residuals, each taking 10 lags. The p values of the Kolmogorov-Smirnov (KS) test (Abadie, 2002) cannot reject the null hypothesis of the standard uniform distribution (0,1) of the probability integral transform of the standardized residuals from the marginal models and correct specification of the marginal distribution model at the 5% significance level (Bernal et al., 2014). These test results verify the adequacy of the skewed Student-t distribution and rule out the possibility of model misspecification.

Table 3.3 Parameter estimates for ARMA-GARCH marginal models of returns

	phi0	phi1	phi2	phi3	theta1	theta2	theta3	w	alpha	beta	υ	λ	LogL	LB(10)	LB^2(10)	ARCH(10)	K-S
PAB	**0.026**							0.017***	0.946***	0.054***	3.904***	0.070***	5582.836	0.189	0.043	0.09	0.46
	(-0.035)							(-0.002)	(-0.003)	(-0.003)	(-0.233)	(-0.017)					
BNB	0.013	0.807***			0.836***			0.068***	0.929***	0.060***	4.357***	0.063***	5707.398	0.216	0.51	0.433	0.891
	(-0.011)	(-0.120)			(-0.111)			(-0.008)	(-0.005)	(-0.005)	(-0.250)	(-0.021)					
SPDB	0.019	-0.660*			0.661*	0.021	0.012	0.023***	0.927***	0.072***	3.878***	0.075***	5313.319	0.782	0.337	0.274	0.154
	(-0.053)	(-0.370)			(-0.373)	(-0.026)	(-0.021)	(-0.004)	(-0.003)	(-0.004)	(-0.231)	(-0.018)					
HXB	0.012							0.030***	0.927***	0.069***	4.357***	0.063***	5421.677	0.511	0.222	0.147	0.222
	(-0.034)							(-0.004)	(-0.003)	(-0.004)	(-0.295)	(-0.020)					
CMBC	0.039	1.293***	1.210***	-0.253	1.301***	1.218***	0.248	0.030***	0.898***	0.102***	4.091***	0.072***	5119.566	0.111	0.081	0.068	0.082
	(-0.114)	(-0.363)	(-0.371)	(-0.323)	(-0.366)	(-0.381)	(-0.333)	(-0.004)	(-0.005)	(-0.006)	(-0.256)	(-0.017)					
CMB	0.02	1.565***	0.921***	-0.008	1.555***	0.912***		0.025***	0.945***	0.050***	4.576***	0.100***	5316.131	0.763	0.895	0.908	0.65
	(-0.012)	(-0.042)	(-0.054)	(-0.022)	(-0.036)	(-0.039)		(-0.004)	(-0.004)	(-0.004)	(-0.291)	(-0.020)					
BNJ	0.047							0.038***	0.931***	0.063***	4.337***	0.061***	5457.476	0.904	0.415	0.37	0.185
	(-0.036)							(-0.006)	(-0.004)	(-0.004)	(-0.265)	(-0.020)					
IBC	0.044							0.012***	0.942***	0.058***	4.464***	0.090***	5371.097	0.023	0.076	0.089	0.057
	(-0.031)							(-0.002)	(-0.004)	(-0.004)	(-0.320)	(-0.017)					
BB	0.018	0.983***	0.385	0.731***	0.965***	-0.414	0.733***	0.012***	0.955***	0.043***	4.084***	0.055***	5204.061	0.282	0.109	0.122	0.223
	(-0.032)	(-0.225)	(-0.399)	(-0.228)	(-0.220)	(-0.388)	(-0.221)	(-0.002)	(-0.002)	(-0.002)	(-0.287)	(-0.018)					
BCM	-0.001	0.096	0.516		-0.069	-0.509	-0.043**	0.052***	0.869***	0.126***	3.940***	0.049**	4899.556	0.072	0.835	0.825	0.975
	(-0.010)	(-0.404)	(-0.365)		(-0.400)	(-0.364)	(-0.020)	(-0.005)	(-0.005)	(-0.006)	(-0.194)	(-0.020)					
ICBC	0.004	-0.052	0.933***	0.003	0.044	0.946***		0.018***	0.902***	0.097***	4.404***	0.059***	4395.071	0.144	0.372	0.55	0.308
	(-0.005)	(-0.062)	(-0.064)	(-0.022)	(-0.059)	(-0.058)		(-0.003)	(-0.004)	(-0.005)	(-0.281)	(-0.020)					
CCB	0.1	0.454***	0.992***		0.476***	1.004***	0.027	0.036***	0.886***	0.107***	4.450***	0.058***	4631.014	0.004	0.736	0.804	0.341
	(-0.061)	(-0.002)	(-0.002)		(-0.022)	(-0.010)	(-0.021)	(-0.004)	(-0.006)	(-0.007)	(-0.268)	(-0.022)					
CB	0.022	0.299***	0.937***	-0.006	0.310***	0.958***		0.028***	0.890***	0.103***	4.198***	0.067***	4317.745	0.25	0.985	0.985	0.852
	(-0.035)	(-0.030)	(-0.026)	(-0.021)	(-0.021)	(-0.019)		(-0.003)	(-0.004)	(-0.005)	(-0.237)	(-0.021)					

CITIB	0.009	0.994**	-0.041	-0.533	-1.001**	0.052	0.501	0.081***	0.901***	0.086***	4.132***	0.086***	5480.358	0.012	0.976	0.987	0.507
	(-0.020)	(-0.415)	(-0.667)	(-0.413)	(-0.423)	(-0.675)	(-0.414)	(-0.010)	(-0.006)	(-0.006)	(-0.272)	(-0.019)					
CITIS	0.044	0.021						0.026***	0.952***	0.046***	4.241***	0.080***	6002.102	0.223	0.294	0.303	0.729
	(-0.043)	(-0.019)						(-0.005)	(-0.003)	(-0.003)	(-0.266)	(-0.023)					
PS	-0.035	-0.316	-0.008	0.003	0.293			0.105***	0.914***	0.074***	4.724***	0.033	6136.979	0.362	0.864	0.849	0.663
	(-0.063)	(-0.688)	(-0.028)	(-0.021)	(-0.688)			(-0.012)	(-0.005)	(-0.005)	(-0.400)	(-0.022)					
SIT	0.021							0.111***	0.947***	0.041***	4.082***	-0.027*	6468.432	0.758	0.952	0.953	0.104
	(-0.053)							(-0.016)	(-0.005)	(-0.004)	(-0.297)	(-0.016)					
SAJ	0.302***	1.930***	0.955***	0.021	1.952***	0.996***		0.178***	0.903***	0.077***	3.623***	0.004**	6201.084	0.479	0.633	0.667	0.069
	(-0.097)	(-0.021)	(-0.041)	(-0.021)	(-0.002)	(-0.002)		(-0.011)	(-0.005)	(-0.005)	(-0.272)	(-0.002)					
ATI	0.044				0.011	-0.016	-0.017	0.063***	0.920***	0.078***	3.218***	0.044***	6146.083	0.172	0.949	0.957	0.396
	(-0.048)				(-0.021)	(-0.022)	(-0.021)	(-0.002)	(-0.002)	(-0.003)	(-0.193)	(-0.012)					
PAI	0.009*	1.831***	0.973***	0.012	1.830***	0.964***		0.034***	0.929***	0.067***	4.705***	0.060***	5583.395	0.122	0.627	0.584	0.245
	(-0.005)	(-0.023)	(-0.040)	(-0.020)	(-0.010)	(-0.010)		(-0.005)	(-0.005)	(-0.005)	(-0.368)	(-0.019)					
CPI	0.001	0.175***	0.307***	0.859***	0.193***	0.290***	0.903***	0.019***	0.954***	0.044***	6.026***	0.051**	5788.121	0.164	0.858	0.913	0.251
	(-0.001)	(-0.051)	(-0.042)	(-0.046)	(-0.043)	(-0.036)	(-0.039)	(-0.006)	(-0.004)	(-0.004)	(-0.622)	(-0.021)					
CLI	0.018	0.971***	0.906***	-0.033	0.980***	0.920***		0.064***	0.924***	0.064***	5.496***	0.095***	5615.5	0.165	0.328	0.335	0.929
	(-0.116)	(-0.031)	(-0.028)	(-0.022)	(-0.024)	(-0.021)		(-0.009)	(-0.006)	(-0.006)	(-0.493)	(-0.022)					
Banks	0.032	0.938***	0.955***		0.939***	0.966***		0.014***	0.929***	0.069***	4.232***	0.092***	4671.127	0.037	0.029	0.034	0.523
	(-0.025)	(-0.017)	(-0.016)		(-0.015)	(-0.014)		(-0.002)	(-0.004)	(-0.005)	(-0.249)	(-0.019)					
Diversified Financials	0.009	0.332	-0.038	0.772***	-0.322	0.033	0.787***	0.019***	0.952***	0.046***	4.558***	0.070***	5821.635	0.252	0.691	0.718	0.746
	(-0.060)	(-0.293)	(-0.336)	(-0.279)	(-0.287)	(-0.329)	(-0.275)	(-0.004)	(-0.003)	(-0.004)	(-0.308)	(-0.021)					
Insurance	0.153	0.967***	0.957***	-0.027	0.971***	0.952***		0.021***	0.940***	0.057***	5.563***	0.069***	5480.176	0.084	0.511	0.425	0.417
	(-0.105)	(-0.026)	(-0.023)	(-0.021)	(-0.016)	(-0.013)		(-0.005)	(-0.005)	(-0.005)	(-0.490)	(-0.022)					

Note: The table presents parameter estimates for the marginal models described in equations (3.1)-(3.3), with z statistics shown under the estimates. LogL is the log-likelihood value; LB(10) and $LB^2(10)$ denote the Ljung-Box statistics for serial correlations in the residual model and squared residual model, respectively, calculated with 10 lags. ARCH(10) denotes the Engle's LM test for the ARCH effects in the residuals up to the tenth order. K-S denotes the p values of the Kolmogorov-Smirnov test for adequacy of the skewed Student-*t* distribution model. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% or 10% significance levels, respectively.

3.4.3 Time-varying copula results

During the sample period, several systemic events occurred and triggered bearish or bullish trends. Periods of high market volatility interspersed with periods of relative calm. Considering the time-varying market conditions and internal structure, we estimate the time-varying versions of copula models where dependence parameters are allowed to be rendered time-varying. The evolution equations for copula parameters are shown in Section 3.3. Model parameters are estimated using maximum likelihood. The best copula fit for each pair composed of a financial institution and its affiliated industry group is selected based on minimum AIC values. Table 3.4 shows the coefficient estimates of the best time-varying copula fits for pairwise returns. Among 22 pairs in total, the best fitting model for 12 pairs is the time-varying Student-t copula (54.5%). The time-varying SJC is the best fit for six pairs (27.3 %), while Gumbel for three pairs and Rotated Gumbel for one pair.

3.4.4 CoVaR and ΔCoVaR results

Determining SIFIs by ΔCoVaR

As larger magnitudes of ΔCoVaR indicate higher risk spillover effects, the financial institution with the largest temporal ΔCoVaR value should be considered to exhibit the highest risk spillover effect on its industry group at the point of time, and be identified as the temporal SIFI. Based on this logic, we use the best time-varying copula fits shown in Table 3.4 to compute temporal ΔCoVaRs of each financial institution to its affiliated industry group, which determines the institution's risk contribution to the system at each time point. We then rank the

Table 3.4 Coefficients estimates of the optimal time-varying copulas

.	Optimal Copula	phi1	phi2	phi3	phi4	phi5	phi6	logL	AIC
PAB-Banks	TVP-SJC	1.597***	-6.851***	0.001***	3.681***	-12.646***	-2.084***	1699.353	-3392.71
		(0.001)	(0.023)	(0.000)	(0.021)	(0.053)	(0.012)		
BNB-Banks	TVP-Student-t	-1.751***	0.034***	4.904***	5.510***			1465.256	-2924.51
		(0.250)	(0.013)	(0.323)	(0.673)				
SPDB-Banks	TVP-SJC	0.886***	-8.757***	1.420***	3.829***	-8.807***	-2.494***	2058.715	-4111.43
		(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)		
HXB-Banks	TVP-SJC	-0.580***	-2.869***	2.566***	1.885***	-10.283***	0.229***	1863.811	-3721.62
		(0.000)	(0.001)	(0.000)	(0.000)	(0.004)	(0.000)		
CMBC-Banks	TVP-Student-t	-1.837	0.093	5	5.295**			1818.931	-3631.86
		(7.190)	(0.544)	(9.262)	(2.479)				
CMB-Banks	TVP-Student-t	-1.653*	0.027	5.000***	4.457***			2090.874	-4175.75
		(0.864)	(0.034)	(1.024)	(0.597)				
BNJ-Banks	TVP-Student-t	1.371	0.017	1.198	4.063***			1620.07	-3234.14
		(4.092)	(0.029)	(4.863)	(0.372)				
IBC-Banks	TVP-Student-t	-1.618	0.046	5	4.849***			2228.09	-4450.18
		(5.432)	(0.045)	(6.116)	(0.634)				
BB-Banks	TVP-Student-t	-1.816***	0.045**	5.000***	4.413***			1643.164	-3280.33
		(0.403)	(0.022)	(0.515)	(0.486)				
BCM-Banks	TVP-Student-t	1.451	0.005	1.505	5.474***			2036.462	-4066.92
		(4.802)	(0.004)	(5.433)	(0.699)				
ICBC-Banks	TVP-SJC	3.857***	-11.756***	-2.437***	2.681***	-9.521***	-1.187***	1724.911	-3443.82
		(0.201)	(1.150)	(0.168)	(0.135)	(0.227)	(0.018)		
CCB-Banks	TVP-Student-t	-1.815***	0.055**	5.000***	5.204***			1691.754	-3377.51
		(0.498)	(0.025)	(0.622)	(0.720)				
CB-Banks	TVP-Student-t	-1.832***	0.062***	4.998***	5.482***			1639.251	-3272.5
		(0.000)	(0.002)	(0.000)	(0.660)				

CITIB-Banks	TVP-Student-t	5.000***	-0.099	-3.014*	4.594***			1560.586	-3115.17
		(1.570)	(0.087)	(1.757)	(0.546)				
CITIS-Diversified financials	TVP-Gumbel	1.321***	0.175***	-3.007***				3169.545	-6333.09
		(0.069)	(0.007)	(0.377)					
PS-Diversified financials	TVP-Student-t	-1.798***	0.038	5.000***	3.340***			1731.953	-3457.91
		(0.528)	(0.024)	(0.665)	(0.297)				
SIT-Diversified financials	TVP-Rotated Gumbel	0.419***	0.351***	-0.801***				934.9506	-1863.9
		(0.056)	(0.016)	(0.153)					
SAJ-Diversified financials	TVP-SJC	0.566	-7.076**	-0.127	2.604***	-11.241***	-1.651*	553.5424	-1101.08
		(0.635)	(3.266)	(0.079)	(0.670)	(2.242)	(0.888)		
ATI-Diversified financials	TVP-SJC	0.659	-7.907***	0.023***	-1.922***	-0.457***	4.003***	537.4421	-1068.88
		(0.415)	(2.234)	(0.008)	(0.033)	(0.139)	(0.047)		
PAI-Insurance	TVP-Gumbel	1.538***	0.157***	-4.664***				3703.426	-7400.85
		(0.054)	(0.004)	(0.455)					
CPI-Insurance	TVP-Student-t	5.000	(0.051)	(2.352)	5.167***			2075.079	-4144.16
		(42.873)	(0.353)	(47.702)	(0.624)				
CLI-Insurance	TVP-Gumbel	1.109***	0.205***	-2.823***				2262.903	-4519.81
		(0.047)	(0.006)	(0.292)					

Notes: This table reports coefficient estimates of the optimal time-varying parameter (TVP) copulas for each pair composed of a financial institution and its affiliated industry group.

financial institutions within each industry group based on the magnitudes of the temporal ΔCoVaR. Those with the highest value of ΔCoVaR are identified as the top risk contributor at that point of time. The dynamics of top risk contributors in each industry group are shown in Figure 3.1, where the left panel shows the evolution in the banking industry, and the upper and lower right panels present the dynamics in Diversified Financials and Insurance, respectively.

Seen in Figure 3.1, financial institutions exhibiting the greatest risk spillovers tend to vary over time. In the presence of this time variation, conclusions cannot be drawn by simply comparing temporal risk contributions across institutions but ignoring the time dimension. A more convenient way is to compare the frequency of each financial institution appearing as the top risk emitter within its industry group during the full sample period.

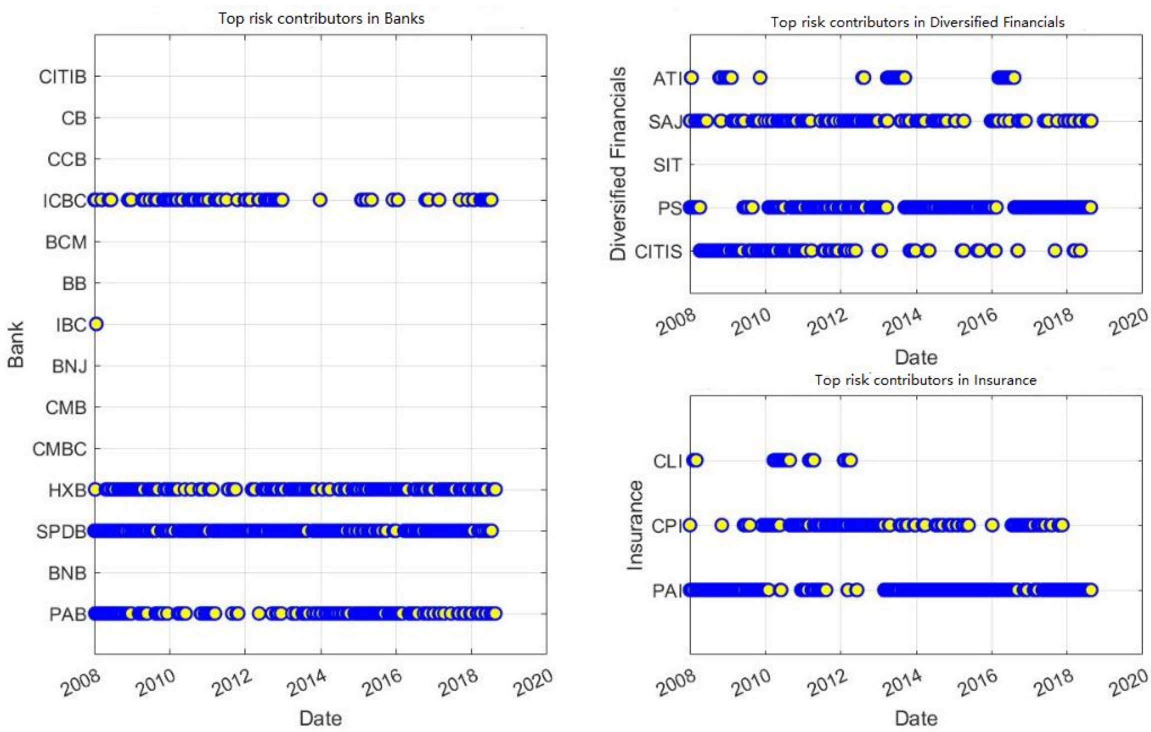


Figure 3.1 Tracking top risk contributors by industry group

Figure 3.2 shows the overall ranking of financial institutions in each industry group in a descending order, according to their frequency of exhibiting temporal highest risk spillover. The left panel shows that among all banks, SPDB has the highest frequency (46.3% over the full sample) of being the top risk emitter in Banks and is identified as the most systemically important bank. Similarly, shown in the upper and lower right panels, PS and PAI are identified as SIFIs in Diversified Financials and Insurance, being the top risk emitter for 49.8% and 62% over the full sample, respectively.

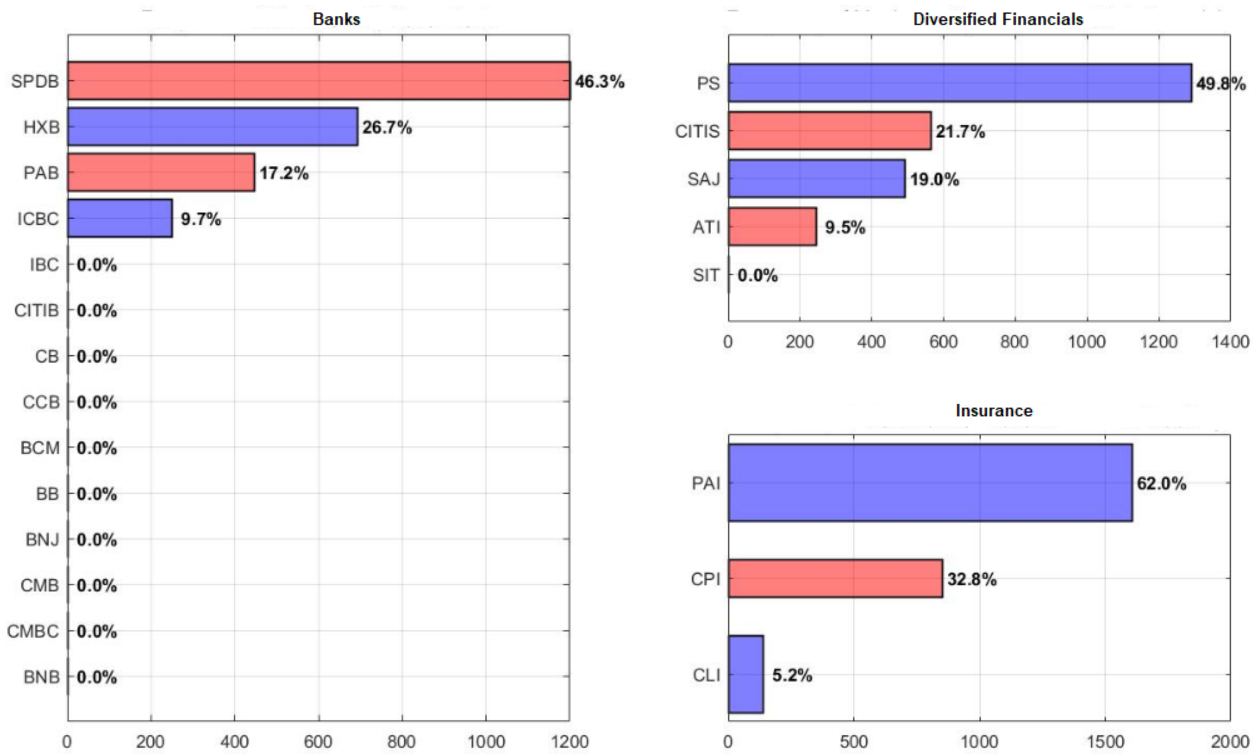


Figure 3.2 Frequency of financial institutions being the top risk contributor by industry group

Given that these three financial institutions, SPDB, PS and PAI, are identified as the SIFI in their own affiliated industry groups based on findings of the copula-ΔCoVaR method, we proceed to analyse the bidirectional risk spillover effects between these SIFIs and their affiliated industry groups. We couple each SIFI with its industry group and form three pairs, and quantify the upside and downside VaRs, CoVaRs and ΔCoVaRs to evaluate bidirectional downside and upside risk spillovers within each pair.

Summary statistics of the average values of the bidirectional upside and downside VaR, CoVaR and ΔCoVaR are reported in in Table 3.5, with standard errors shown in the parentheses. Panel A reports risk spillovers from SIFIs to their corresponding industry groups, while Panel B reports risk spillovers from the opposite direction.

Table 3.5 Summary statistics for the VaRs, CoVaRs and △CoVaRs

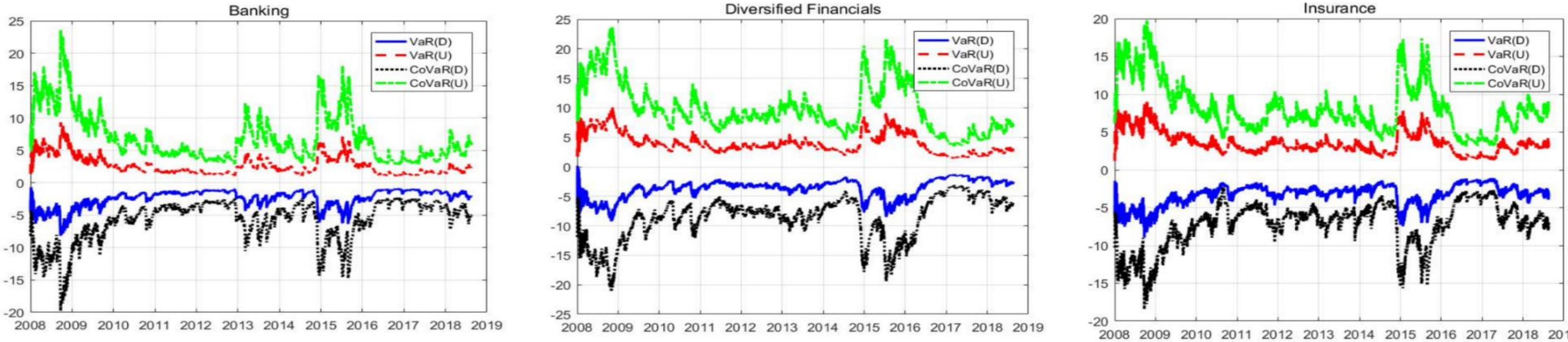
	Downside			Upside		
	VaR	CoVaR	△CoVaR	VaR	CoVaR	△CoVaR
Panel A: VaR of SIFI returns, CoVaR and △CoVaR from SIFI to its industry group						
Banks ← SPDB	-2.395	-5.878	0.925	2.650	6.947	1.007
	(1.300)	(3.146)	(0.055)	(1.417)	(3.713)	(0.059)
Diversified Financials ← PS	-3.697	-8.749	0.875	3.961	9.903	0.941
	(1.579)	(3.679)	(0.118)	(1.680)	(4.153)	(0.053)
Insurance ← PAI	-3.282	-7.236	0.758	3.533	8.209	0.826
	(1.357)	(2.972)	(0.081)	(1.436)	(3.289)	(0.056)
Panel B: VaR of industrial returns, CoVaR and △CoVaR from the industry group to its SIFI						
Banks → SPDB	-3.002	-7.787	1.001	3.302	8.989	1.063
	(1.537)	(3.941)	(0.414)	(1.652)	(4.528)	(0.244)
Diversified Financials → PS	-4.277	-10.092	0.861	4.360	10.629	0.904
	(1.802)	(4.241)	(0.045)	(1.855)	(4.485)	(0.046)
Insurance → PAI	-3.364	-7.941	0.854	3.628	8.960	0.918
	(1.402)	(3.283)	(0.092)	(1.476)	(3.602)	(0.062)

Notes: This table reports the average values of the bidirectional downside and upside VaR, CoVaR and△CoVaR of the SIFIs and corresponding industry groups. Panel A reports the risk spillovers from SIFIs to their affiliated industry groups, while Panel B reports risk spillovers from the opposite direction.

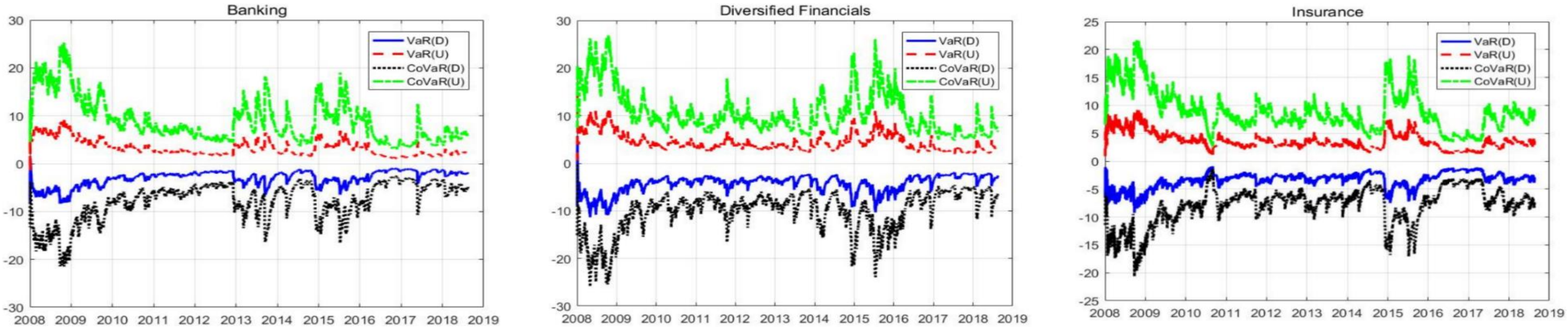
Risk spillovers from SIFIs to the financial system

For more in-depth analysis on risk spillovers, we examine the directional risk spillovers from SIFIs to the financial system. Specifically, it is measured by risks transmitted from SIFIs to their corresponding industry groups, forming totally three pairs, namely, from SPDB to Banks, from PS to Diversified Financials, and from PAI to Insurance.

Panel A of Figure 3.3 depicts the dynamics of upside and downside VaRs vis-à-vis CoVaRs for all three pairs during the full sample period. Notably, all pairs exhibit a common pattern that the downside CoVaRs are systemically below the downside VaRs over the full sample period. We corroborate this finding by the Kolmogorov-Smirnov (KS) test, as these differences are reported as significant by the test in all cases, shown in column 2 of Panel A of Table 3.6. This indicates that extreme downward movements in SIFIs' returns have spillover effects on their corresponding industrial indices, whose VaRs drop by significant amounts following the extreme downturns of SIFIs' returns, although to different extents (measured by the magnitude of CoVaR) across industry groups. Similarly, the average upside CoVaR values are systemically greater than the average upside VaR values despite different magnitudes, also corroborated by the KS statistics reported in column 3 of Panel A in Table 3.6. It provides evidence of upside risk spillovers from the SIFIs to the financial system, meaning that extreme upward movements of SIFIs' returns have significant positive impacts on the returns of the industry and the broader financial system.



Panel A: Upside and downside VaRs of SIFI returns and CoVaRs from SIFIs to affiliated industry groups



Panel B: Upside and downside VaRs of industrial returns and CoVaRs from industry groups to corresponding SIFIs

Figure 3.3 Upside and downside VaRs and CoVaRs between SIFIs and the financial system

Table 3.6 Tests of risk spillovers and asymmetric downside and upside effects

	Downside	Upside		
	H0:CoVaR=VaR H1:CoVaR<VaR	H0:CoVaR=VaR H1:CoVaR>VaR	H0:CoVaR/VaR(Down)=CoVaR/VaR(Up) H1:CoVaR/VaR(Down)<CoVaR/VaR(Up)	H0:DeltaCoVaR(Down)=DeltaCoVaR(Up) H1:DeltaCoVaR(Down)<DeltaCoVaR(Up)
Panel A: VaR of SIFI returns, CoVaR and △CoVaR from SIFI to its industry group				
Banks ← SPDB	0.657***	0.692***	0.662***	0.686***
	(0.000)	(0.000)	(0.000)	(0.000)
Diversified Financials ← PS	0.688***	0.713***	0.634***	0.654***
	(0.000)	(0.000)	(0.000)	(0.000)
Insurance ← PAI	0.686***	0.718***	0.419***	0.456***
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: VaR of industrial returns, CoVaR and △CoVaR from the industry group to its SIFI				
Banks → SPDB	0.664***	0.693***	0.915***	0.929***
	(0.000)	(0.000)	(0.000)	(0.000)
Diversified Financials → PS	0.746***	0.759***	0.738***	0.755***
	(0.000)	(0.000)	(0.000)	(0.000)
Insurance → PAI	0.720***	0.737***	0.367***	0.406***
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: This table reports the Kolmogorov-Smirnov statistics for testing the bidirectional downside and upside risk spillovers, as well as symmetry of upside and downside CoVaRs and △CoVaRs. Panel A reports the test results for risk spillovers from SIFIs to their affiliated industry groups, while Panel B reports results for risk spillovers from the opposite direction.

These findings can be of great assistance for stock market investors looking for potential investment opportunities in the financial assets in the Chinese stock market during asset allocation and risk hedging. Regarding downside risk spillovers from SIFIs to the financial system, portfolios composed of assets diversified across industry groups may still be highly susceptible to systemic risk contributed largely by the SIFIs. Simply holding portfolios composed of non-SIFI stocks is rarely enough to protect portfolios against downside risks transmitted from SIFIs to the whole financial sector, which all stocks are exposed to. Investors should consider downside risks of both the SIFIs and the affected industry groups and take short positions on SIFIs' returns, to hedge downside risk spillovers. For upside risk spillovers, the practical implications are similar, but considering taking long rather than short positions on SIFIs' returns.

Risk spillovers from the financial system to SIFIs

Considering risk spillovers from the financial system to SIFIs, the movements of VaRs and CoVaRs again exhibit similar trends in both downside and upside cases during the sample period based on the graphic evidence in Panel B of Figure 3.3. Overall, SIFIs' returns are significantly affected by risk spillovers from the financial system. Considering downside risk spillovers, downside VaR values are above the downside CoVaR values in a systematic and significant fashion for all three pairs, corroborated by the KS statistics reported in column 2 of Panel B of Table 3.6. This implies that extreme downturns in the industrial indices have significant negative systemic impacts on SIFIs' returns. This can be explained by the phenomenon that substantial or extreme reduction in industrial indices triggers low market valuations and investors' expectation of a bearish trend. Due to the flight-to-quality effect

(Bernanke et al., 1996), capital flows out from the financial sector, leading to a considerable drop in stock prices and returns of SIFIs.

Regarding upside risk spillovers, the average values of upside CoVaR are systemically and significantly higher than upside VaR, confirmed by the KS test results in column 3 of Panel B of Table 3.6. This indicates that extreme upward movements in sectoral/industrial returns are accompanied by a significant increase in SIFIs' returns, proving existence of upside risk spillover effects from the financial system to SIFIs. The extreme upward movements in industrial returns have positive impacts on SIFIs' returns. This can be plausibly explained by the trend-chasing effect (Orosel, 1998) that capital flows into these industry groups and the sector as a whole, incentivized by excessively soaring industrial and sectoral indices, which leads to a bullish market condition and significant increases in SIFIs' returns. For stock market investors, by looking at the downside and upside VaR and CoVaR measures, they can assess to what extent the portfolio might be affected by extreme movements in the sectoral/industrial indices to facilitate better asset allocation across sectors and industry groups.

Asymmetric risk spillovers

In addition, upside and downside risk spillover effects are shown to be asymmetric in the bidirectional risk spillover cases. We confirm this asymmetry by testing the significant differences between the downside CoVaRs normalized by the downside VaRs and the upside CoVaRs normalized by the upside VaRs. The KS test results are summarized in column 4 of Table 3.6. The KS statistics provide evidence that there exists significant asymmetry between normalized downside and upside CoVaRs, suggesting asymmetric downside and upside risk spillover effects from the SIFIs to the financial system and vice versa.

Considering risk spillovers from the SIFIs to the financial system, the results in column 4, Panel A of Table 3.6 imply that SIFIs' downward systemic impacts on the financial system are lower than its upward systemic impacts, and market participants may be more susceptible to upside than downside risks passing down following the SIFIs' extreme movements. A plausible explanation can be the asymmetric reactions by investors between upward and downward extreme conditions when taking momentum investing strategies. Given upside risk spillovers, excessively high SIFI returns cause capital to flow into its affiliated industry due to the trend-chasing effect, boosting a bullish market and an overall upward movement of sectoral returns. In an opposite scenario, investors perceive high risks signalled by abruptly declined SIFI returns, leading to capital outflows from the SIFIs and the wider system due to the flight-to-quality effect and pessimistic sentiment among investors, pushing down the market to a bearish status.

Likewise, in the cases of risk spillovers from the financial system to the SIFIs, downside risk spillovers are lower than upside risk spillovers, corroborated by the KS statistics shown in column 4, Panel B of Table 3.6. Empirical results imply that capital outflows following extreme sectoral downturns can affect SIFIs' returns to a lower extent than capital inflows following soaring sectoral indices. In other words, SIFIs' returns are more affected by upward than downward systemic impacts from the financial system. This again can be interpreted as investors in the Chinese stock market seem to react more to bullish than to bearish signals, and more to good than to bad news. A plausible explanation based on the behavioural finance theory can be the disposition effect (Shefrin and Statman, 1985), where investors hold back from selling despite bearish market signals, which offsets the flight-to-quality effect and alleviates the effect of downside risk spillovers from the financial system to SIFI returns.

ΔCoVaR analysis

The average values of upside and downside ΔCoVaRs for bidirectional spillovers are reported in Table 3.5 and depicted in Figure 3.4. The average downside ΔCoVaR values are shown to be lower than average upside ΔCoVaR values in all cases. These significant differences are corroborated by the KS test statistics reported in column 5, Table 3.6.

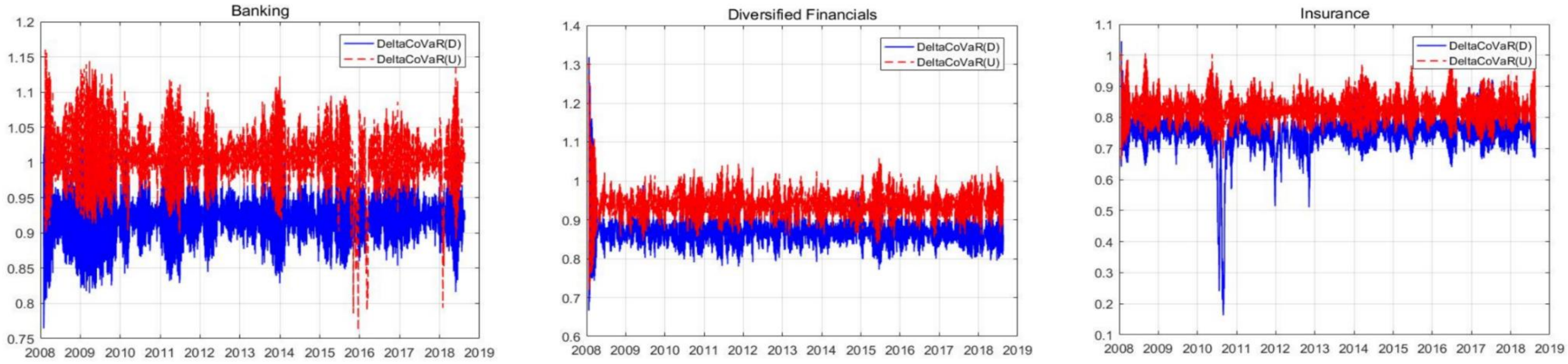
These findings of the asymmetric downside and upside ΔCoVaRs are consistent with our previous results obtained by quantifying the bidirectional CoVaRs. The asymmetric downside and upside CoVaRs and ΔCoVaRs both demonstrate that upside systemic impacts exceed their downside counterparts in all cases. These findings provide evidence that changes in capital flows in the stock market and investors' expected returns reinforce upside risk spillovers to a greater extent than downside spillovers in the Chinese financial system, and suggest a stronger trend-chasing effect than the flight-to-quality effect, as the latter is possibly offset by the disposition effect among China's market participants. Consistent with the argument in the extant literature, we find that besides market fundamentals, other factors such as investors' sensitivities to news and their sentiment affect and enhance risk spillovers patterns (Reboredo et al., 2016; Mensi et al., 2017). While several other studies find evidence of stronger market reactions to bearish news in other markets (Reboredo et al., 2016; Jin, 2018), we find that investors in the Chinese market exhibit more sentiment to market upturns than to downturns, and react more to good news than to bad news. These differed reactions thus make the whole system more sensitive to extreme upturns (upside risk) than downturns (downside risk).

3.5 Conclusions

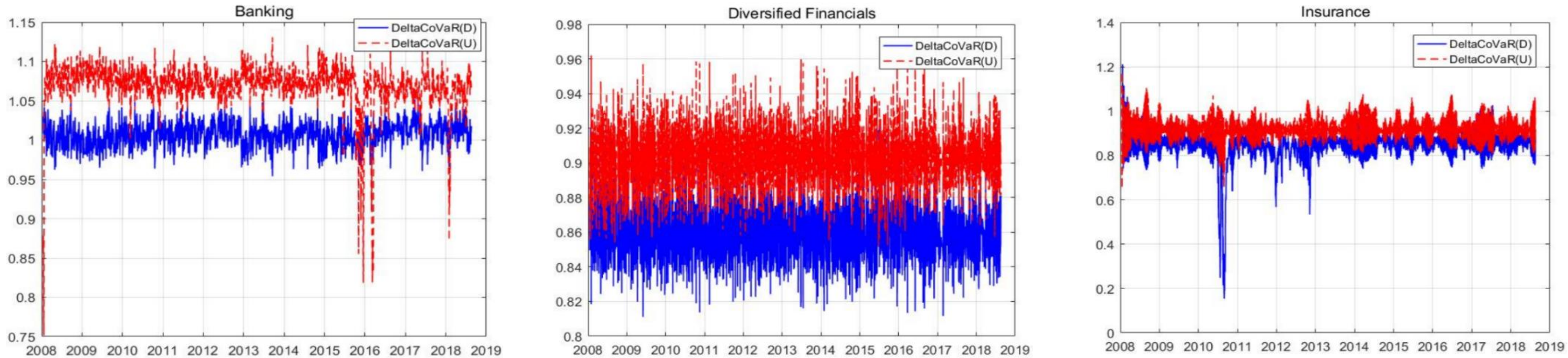
In this study, we attempt to identify the systemically important financial institution (SIFI) based on the CoVaR values of firms to their corresponding industries, and further examine upside and downside risk spillovers between those identified SIFIs and the financial system as a whole.

Our empirical analysis shows that Shanghai Pudong Development Bank (SPDB) is the most systemically important financial institution in China's Banking industry, as it exhibits the strongest risk spillover effects on the industry over the full sample period. While from a global perspective, CB, ICBC, Agricultural Bank of China and CCB are identified as G-SIBs (FSB, 2018), our analysis finds evidence that within the banking sector in China, SPDB exhibits the highest systemic importance. This difference may be attributed to different business focuses and expansion modes between the G-SIBs and the domestic SIFI, which can be of further research interest.

Similarly, Pacific Securities Co., Ltd. (PS) and Ping An Insurance (Group) Co. of China, Ltd. (PAI) are identified as SIFIs for Diversified Financials and Insurance, respectively. The latter is consistent with the ranking shown in the 2016 G-SIIs list (FSB, 2016), implying PAI's systemic importance in both local and global contexts.



Panel A: △CoVaR from SIFIs to affiliated industry groups



Panel B: △CoVaR from industry groups to corresponding SIFIs

Figure 3.4 Upside and downside △CoVaR between SIFIs and the financial system

We further find strong evidence of bidirectional downside and upside risk spillovers between the recognized SIFIs and the financial system. Our findings are consistent with the phenomena that while SIFIs as individual institutions, their returns tend to co-move with the sectoral/industrial trends, their own extreme movements can also trigger market reactions and significantly affect sectoral returns as a result of their non-negligible systemic importance. Based on these results, we argue that information sets reflected in extreme movements send signals across the market and direct the actions of investors, which have a strong predictive power of the performance of affected components in the financial system.

We also find that the risk spillover effect in the Chinese financial system has been notably stronger during the 2008 global financial crisis, indicating strengthened risk influence from the global market to the Chinese market because of increasing integration of China's economy into the world economy. Also, during the Chinese stock market turbulence periods in 2009, 2013 and 2015, systemic risk spillovers are shown to be remarkably stronger than during calm periods, implying increased risk flows between the stock market and the financial sector, which can be a topic worth further exploring.

Our results reveal that downside and upside risk spillovers are asymmetric, with upside spillover effects being stronger than their downside counterparts in all cases. This asymmetry plausibly indicates a stronger presence of the trend-chasing effect than the flight-to-quality effect in the Chinese financial system, and also implies the role of the disposition effect in mitigating sudden downturns caused by downside risk spillovers.

Our findings can substantially aid investors in asset allocation and risk management. All market participants should be alerted to the bidirectional risk spillovers in the financial system. They should also consider the asymmetric patterns of risk spillovers and accordingly hedge and adjust their positions to reduce risk exposure of portfolios. From the regulatory and supervisory perspectives, identifying SIFIs and the risk spillover trajectories is of great importance. Our finding seeks to help regulators improve the governance of the financial sector and impose proper macro-prudential regulations to bolster financial stability. First, it helps policy practitioners precisely identify the most influential risk elements in the financial sector, which act as the bellwether dominating the systemic risk flows and leading the trend of movements of many others and the entire system at large. Second, policies and regulations will be able to target the riskiest parts of the system and take pre-emptive actions before systemic risk escalates to impair the functioning of the financial system.

4 Stock market integration or empirical fallacy? Evidence from East and Southeast Asia

This chapter explores the issue of financial integration among stock markets of ASEAN5 economies, plus China (mainland China and Hong Kong), Japan and South Korea (referred to as ASEAN5+4)[16]*. Using both a minimum spanning tree and a vector autoregressive (VAR)-based method accompanied by rolling window analysis, we show that the level of interconnectedness among these markets is high but with clear time-varying patterns. A large share of this seemingly high level of integration is shown to be driven by common global factors. After filtering these factors from each stock market, the magnitude of interconnectedness falls substantially. Our results therefore suggest that stock market integration in East and Southeast Asia is not as strong as it looks. Although governments in this region have been promoting financial market collaboration and integration, barriers remain significant. The overestimated interconnectedness is mainly a simple reflection of stronger global influences on individual markets over time, while their interconnectedness attributable to non-global factors shows a descending trend after the global financial crisis and its aftermath.*

[16] Chapter 4 is based on a published article Wu (2019b) in *International Review of Financial Analysis*, doi.org/10.1016/j.irfa.2019.101416.

4.1 Introduction

Asian stock markets are usually said to be increasingly integrated in recent years (Chien et al., 2015), accompanied by joint policy efforts on building up a regionally integrated market to promote capital mobility within the region, such as the ASEAN Economic Community (AEC) Blueprint series (ASEAN, 2015). Regional stock market integration was found to be even more reinforced during the turmoil of the global financial crisis (Gupta and Guidi, 2012; Caporale and You, 2017). For the post-crisis period, while some studies find evidence of declining co-movement among certain Asian stock markets (Gupta and Guidi, 2012), others find strengthened linkages among major East Asian stock markets (Wang, 2014).

Capital market liberalization and globalization largely contribute to Asian stock market integration (Arouri and Foulquier, 2012). With on-going financial market deregulation and capital account liberalization, cross-border financial transactions are more prevalent (Singh, 2009; Chien et al., 2015). Massive inflows of foreign investment contribute substantially to the boom of local equity markets in this region. Market capitalization of major Ease and Southeast Asian stock markets grows considerably over the last two decades. During our sample period, the market value rises 6.51 times for Hong Kong, 9.48 times for Indonesia, 6.06 times for the Philippines, and a whopping 61.13 times for China's A-share market, with its Shanghai stock Exchange being the fourth largest in the world by the end of 2018[17]. East and Southeast Asian stock markets have become an important part of fund managers' international portfolios for the

[17] Source: Statistia, https://www.statista.com/statistics/270126/largest-stock-exchange-operators-by-market-capitalization-of-listed-companies/, last retrieved on 10 July 2019.

purposes of increasing returns and reducing risks (Jan et al., 2000; Johnson and Soenen, 2002; Narayan et al., 2014).

It is not surprising that the global stock market exerts increasingly significant influences on Asian markets when massive capital keeps flowing into the Asian markets (Huyghebaert and Wang, 2010; Burdekin and Siklos, 2012). Shown in the 2018 Asian Economic Integration Report (ADB, 2018), Asia's economic integration with the world has been largely enhanced in recent years. According to the report, Asia's cross-border asset holdings continued to grow from 13.2 to 17 trillion USD between 2012 and 2017, more than 75% of which were from outside the region. Asia' share of global inward foreign direct investment has shown an increasing trend, rising from 27.8% in 2016 to 36.2% in 2017. This year also witnessed a surge of global remittances to Asia amounting to 272.5 billion USD, concurrent with strengthened global economy. An upward trend is also seen in international holdings of Asian portfolio equity assets, rising by 1.3 trillion USD in 2017, more than the combined increase over the past four years. Although cross-border portfolio equity holdings in Asia increased substantially between 2012 and 2017 by 2.2 trillion USD with a significantly increased share in total cross-border assets (from 17.1% to 26.2%), the intraregional share, however, decreased from 25.6% to 18.1%.

There is no doubt that the trend of globalization inevitably leads to significantly increased stock market co-movement (Beine et al., 2010) and stronger linkages in capital markets arising from potential spillover effects on domestic markets (De la Torre et al., 2007). It is, however, questionable how strong Asian equity markets are interlinked in the absence of common global factors. In other words, are regional stock markets intrinsically getting more integrated, or is it simply due to unaccounted information, most notably, common factors of the global market?

The logic behind this argument is that capital markets are not completely liberalized in the Asian economies, especially the Chinese and ASEAN markets, which are at different stages of development and have substantial differences in market practices, legal environments, regulatory frameworks and intuitional development (Singh, 2009). It is rather difficult for investors to switch their investment from one market to another in the presence of capital restrictions and also exchange rate risks. The extant empirical evidence of increasing stock market co-movement may simply reflect an increasing influence from global systemic risk on individual markets. If a group of economies are commonly prone to pervasive global influences, it is well expected to see a high level of integration among their stock markets (Pukthuanthong and Roll, 2009).

We therefore argue that failing to account for the contributions of global common factors can lead to biased conclusions on the level of cross-market connectedness attributable to regional or local factors. The main purpose and contribution of this study are to examine how much global common factors tend to affect regional stock market integration. Inspired by the global capital asset pricing model (GCAPM) (among others, Bhattacharya and Daouk, 2002; Carrieri et al., 2007; Arouri and Foulquier, 2012; Alotaibi and Mishra, 2017), we view individual stock markets as constituent assets of a portfolio, and the world stock market influence as a systematic factor. Using a simple market model, we manage to remove the global influence from local stock markets to further reinvestigate their interconnectedness, which we refer to as a filtering process.

Since the early 1990s, Asia has been riding on a wave of rapid economic growth, attracting increasing investment and trading flows. The phenomenal regional development has been characterized as the Asian miracle, where the ASEAN5 economies, alongside Hong Kong and South Korea are referred to as the new emerging tigers. The 1997-98 Asian financial crisis not only severely hit most East and Southeast Asian economies leading to economic and political turmoil in some countries, but also induced financial contagion that raised fear of a worldwide economic meltdown. Since then, leaders of these governments have been striving for regional economic and financial integration, seen in for example, the Chiang Mai Initiative (CMI) introduced in May 2000 aiming to establish a regional coalition force to cope with short-term liquidity problems.

Among the studies focusing on East and Southeast Asian stock markets, most of them seek to explore the interconnectedness and integration between China and ASEAN5 (Jayasuriya, 2011; Chien et al., 2015). Our study seeks to investigate the integration of the ASEAN5 and four major East Asian stock markets, including Japan, China (mainland China and Hong Kong), and South Korea, from 1999 to 2019. The Association of Southeast Asian Nations (ASEAN) was founded on 8 August 1967 and first included five member countries (Indonesia, Malaysia, the Philippines, Singapore and Thailand, referred to as ASEAN5). By the end of 2018, the ASEAN5 countries constitute 73.6% of the total ASEAN population and 87.45% of GDP[18]. On the other hand, East Asia has been a most prominent sub-region in Asia being both a popular source and destination for intraregional portfolio investment (ADB, 2018), where Japan, China and South Korea are leading and most influencing economies in this region. More than 20 years

[18] Source: Statistia.

after the Asian financial crisis, these major Asian stock markets have exhibited increasing importance to the regional and global economy. A sample composed of these economies is worth investigating and this study seeks to render useful information to potential users.

In terms of methodology, we start from a simple correlation analysis and extend to the classic minimum spanning tree (MST) based on graph theory to visualize the interdependence structure among the ASEAN5+4 stock markets. The leading stock markets which play critical roles in connecting other markets in the network are identified by the MST. Considering the profound and long-lasting influence of the 2008 financial crisis on the global economy and equity markets, the analysis is conducted for the full sample and two subperiods divided by a date based on the Lehman Brothers episode (15 September 2008). To test the robustness of the correlation and MST results, we use a recently developed multivariate time series approach proposed by Diebold and Yilmaz (2014) to construct a connectedness matrix and find the total connectedness in the system. A rolling-window approach is adopted to depict how the interconnectedness evolves over time, to complement to the static description of the full sample.

We find evidence of time-variant interconnectedness, with the importance of individual markets (nodes) and links among them varying over time. There are substantial differences across these stock markets in terms of their level of integration. Singapore is on average the most integrated stock market over the full sample, playing a critical role in connecting all markets and is also most exposed to information spillovers from others, based on both filtered and non-filtered analyses. This confirms the extant evidence that Singapore plays a gatekeeper role for many Asian markets (Chowdhury et al., 2019). Mainland China, despite its big market value, is among the most segmented, which is in line with the argument that its big internal market tends to offset its dependence on global financial and economic shocks, notwithstanding its increasingly significant role in the global economy (Aityan et al., 2010). Together with Japan, these two are on average the biggest markets but are meanwhile the least integrated, implying that market size seems not to be a critical factor affecting a local market's level of integration.

In contrast to the general perception that domestic stock markets in Asia are becoming more integrated, our results suggest that it is not exactly the case. Although none of these stock markets appears to be completely segmented, the level of cross-market integration in this region is shown to be quite low after we manage to filter out the influences from the world stock market. The interconnectedness in the system is increasingly overestimated over time, implying that the ASEAN5+4 stock markets are becoming more exposed to some common world stock market factors, whilst their intrinsic interconnectedness attributable to non-global factors shows a descending trend after the crises.

The remainder of this chapter is organized as follows. Section 4.2 reviews the related literature. Section 4.3 introduces the main methodologies adopted in this study. Section 4.4 presents the data. Section 4.5 discusses the results from the empirical analysis. The final section concludes with some practical implications.

4.2 Literature review

The evolution of stock market integration is a complex, gradual and time-varying process, with occasional reversals (Bekaert and Harvey, 1995). The degree and time variation of global or regional stock market integration are affected by both institutional and behavioural factors and are subject to on-going economic, political and institutional reforms. Financial market development and financial liberalization progress significantly bolster stock market integration, by reducing barriers to portfolio flows and increasing availability of market substitutes (Carrieri et al., 2007). With increased accessibility for global investors to the domestic stock market, or from the opposite direction, domestic investors' ability to access foreign investment opportunities, domestic assets are inevitably more exposed to information spillovers and shocks from foreign markets, leading to a more integrated domestic stock market into the regional or global market (Arouri and Foulquier, 2012).

There exists a general consensus that financial market integration brings benefits to the long-term development of the economy and domestic stock market, such as increasing investment opportunities, lowering the cost of equity capital, improving corporate and public governance, and promoting international risk sharing, especially for emerging markets (Bekaert and Harvey, 2003; Chari and Henry, 2004; Carrieri et al., 2007; Lehkonen, 2014). For policy makers, a more integrated financial market can contribute to more diversified sources of financing and investment channels, broadened investor base and range of financial products, and reduction in stock return volatility (Singh, 2009; Umutlu et al., 2010; Esqueda et al., 2012). Financial market integration helps strengthen domestic capital markets to enable them to compete globally, lessen asymmetric shocks, improve the shock-absorbing capacity of the economy and mitigate risks arising from cross-border financial contagion, therefore bolstering financial stability (Singh, 2009; Beine et al., 2010; Narayan et al., 2011). From an investor's perspective, it enables investors to actively seek for worldwide investment opportunities to increase international portfolio diversification benefits and achieve efficient capital allocation (Chien et al., 2015). Some studies, however, find that international portfolio diversification benefits tend to decline as cross-market financial integration increases (Billio et al., 2017).

4.2.1 Global integration

Among the voluminous amount of literature on stock market integration, many studies seek to focus on global integration. Labidi et al. (2018) examine the time-varying cross-quantile dependence between developed and emerging stock market returns during the aftermath of the global financial crisis by incorporating uncertainty measures and recursive sampling, and find heterogeneous quantile relations of the US, UK German and Japanese stock market returns to those of emerging markets. Mobarek et al. (2016) explore the determinants of stock market co-movement and cross-market linages among ten developed and ten emerging stock markets during both turbulent and non-crisis periods from 1999 to 2011, by a DCC-MIDAS approach. Al Nasser and Hajilee (2016) explore integration among five emerging stock markets and with the US, UK and German markets from 2001 to 2014, and find evidence of short-run integration among all markets, but a significant long-run relationship of all emerging market indices with only the German stock market index.

Chen et al. (2014a) study the integration between frontier and leading stock markets using the Granger-causality test, and find by logit regression model the significant roles of several country-level macroeconomic variables in affecting their integration. Kenourgios et al. (2011) estimate the dynamic non-linear correlations between the BRIC markets and the US and UK markets from 1995 to 2006 covering five recent financial crises, based on a multivariate regime-switching Gaussian copula model and the asymmetric generalized dynamic conditional correlation (AG-DCC) approach. They find evidence of contagion from the crisis country to others, where BRIC markets are more prone to financial contagion. Chen (2018) uses a Bayesian dynamic latent factor model and finds that regional and global common factors can simultaneously affect stock markets across the world, leading to increasing linkages and co-movements among these markets. The effects of these common factors, however, are found to differ across stock markets in different regions and between developed and emerging markets. The co-movement of a domestic stock market with the international stock market is also determined by the level of the country's integration into the global economy.

4.2.2 Emerging markets

Emerging market integration has also been intensively discussed in the relevant literature. One strand of literature explores the integration and interconnection among emerging markets in countries within a geographic region, or a regional intergovernmental political and economic union. Alotaibi and Mishra (2017) employ an international asset pricing model and a DCC-GARCH model to investigate the financial integration for the GCC stock markets. The authors find significant and positive impacts of trade openness, financial market development and turnover, and oil revenue on market integration, as well as the significant and negative impacts of the global financial crisis.

Another strand of literature studies the integration between emerging and developed western stock markets. Gilmore and McManus (2002) find evidence of low short-term correlations and no long-term relationship between three Central European stock markets and the US market by the Johansen cointegration test, and Granger causality from the Hugarian to the Polish market from 1995 to 2001, suggesting international portfolio diversification benefits from these emerging Central European markets for US investors. Guidi and Ugur (2014) find evidence of integration between five South-Eastern European (SEE) stock markets and their developed counterparts (Germany, the UK and US) using both static and dynamic cointegration analysis over 2000-2013, especially during crisis periods. Yarovaya and Lau (2016) apply conventional and regime-switch cointegration methodologies to the UK, BRICS and MIST stock markets, and suggest no evidence of diversification benefits for the UK investors by holding a portfolio in the BRICS and MIST emerging markets, while the Chinese stock market is shown to be the most attractive option. The authors also apply the AG-DCC method and find evidence of higher dependency among the stock markets when it is driven by negative shocks to the market, as well as some evidence in favour of the decoupling hypothesis that emerging markets are driving the dynamics of the world economy.

4.2.3 Asian markets

Earlier empirical evidence shows that emerging Asian markets usually have a low level of exposure to global factors or integration with western developed markets (Harvey, 1993). More recent evidence, however, suggests that Asian stock markets tend to follow some leading western developed markets, most likely, the US market (Aityan et al., 2010). The integration of Asian stock markets with each other as well as with developed western stock markets are discussed by many.

Jiang et al. (2017) find that the 2008 financial crisis reinforces the interdependence among six major stock markets (mainland China, Hong Kong, Japan, Germany, the UK and US), with general co-movements in the global stock market remaining persistent even after the crisis, using a vector auto-regression model and the Granger causality test. Gupta and Guidi (2012) use cointegration methodology to explore the interdependence between the Indian stock market and three developed Asian markets (Hong Kong, Japan and Singapore), and the dynamic conditional correlation among these markets from 1999 to 2009. They find that the time-varying correlation increases dramatically during crisis periods and declines to pre-crisis levels after the crisis, providing evidence of short-term relationships but no long-run linkages across these markets.

Huyghebaert and Wang (2010) study the time-varying interdependence among seven major East Asian stock markets (mainland China, Hong Kong, Taiwan, Singapore, South Korea, Japan) focusing on the impacts of the 1997-98 Asian financial crisis, and find significant roles of the Hong Kong and Singapore markets during and after the crisis, as well as the strong influences of the US market on all East Asian markets except for the Mainland China market during all periods. Wang (2014) finds strengthened linkages among six major East Asian stock markets after the 2008 global financial crisis, and declining influences of the Hong Kong, Singapore and US stock markets on East Asian stock markets but increasing importance of South Korea and Japan after the crisis.

By contrast, Burdekin and Siklos (2012) find evidence of integration of the Chinese stock market with the US market and many regional stock markets from 1995 to 2010. Guidi et al. (2016) investigate the dynamic co-movements among the Greater China region (Mainland China, Hong Kong and Taiwan) and the UK and US stock markets, and find only intermittent episodes of cointegration among market indices, and positive but low and insignificant conditional correlations between market returns, indicating possible diversification benefits for the UK and US international investors by holding stocks issued in the Greater China region.

Among the sparse studies focusing on East and Southeast Asian stock markets, most seek to explore the interconnectedness and integration between China and ASEAN5. Chien et al. (2015) investigate the dynamic convergence among the Chinese and ASEAN5 stock markets using recursive cointegration analysis. They find evidence of gradually increased regional financial integration. Jayasuriya (2011) uses a VAR model to investigate the interlinkages between China's stock market and three neighbour emerging markets, Thailand, Indonesia and the Philippines, from 1993 to 2008, and finds no significant evidence of interrelation in the aggregate market unless taking foreign investors' returns into account, but evidence of shock transmission from China to the others.

Motivated by these studies, we extend the scope by encompassing the most important (and also the biggest) stock markets in this region, including those of ASEAN5 plus Japan, Hong Kong, mainland China and South Korea, to depict the cross-market interdependencies in Asia, hoping to provide useful implications to both policy makers and market participants.

4.3 Methodology

4.3.1 VAR-based approach

Reviewing the literature, a battery of econometric techniques have been applied to studying equity market integration and interdependencies, including the generalized autoregressive conditional heteroscedasticity model (GARCH) (Jayasuriya, 2011; Sewraj et al., 2018), dynamic conditional correlation (DCC) (Mobarek et al., 2016), cointegration test (Chen et al., 2014a; Zhang and Li, 2014), quantile regression (Zhang and Li, 2014), cross quantile dependence/correlation (Labidi et al., 2018), multi-factor R-squared approach (He et al., 2015), Bayesian dynamic latent factor model (Chen, 2018), time-varying copula (Kenourgios et al., 2011; Wang et al., 2011; Hussain and Li, 2018), etc. Billio et al. (2017) compare the performance of a wide range of measures describing several dimensions of financial integration by applying these measures to country groups composed of developed markets, emerging markets, or a group of both, and find that all measures similarly show a long-run integration pattern. Yu et al. (2010) survey the various indicators used in Asian equity market integration studies, and categorize them into six groups: cross-market return dispersion, the Haldane and Hall (1991) filter method, dynamic cointegration analysis, common component approaches, market cycle synchronization and the dynamic conditional correlation (DCC) method.

Drawn on the seminal work of Allen and Gale (2000b), the network theory has been inspiring the exploring and modelling of interconnectedness in financial markets and the structural vulnerability that may induce risk propagation and imperil system-wide stability. More recent studies in this vine focus on identifying potential interconnectedness among financial institutions that may induce or facilitate risk contagion and amplification based on quantitative network methods, so as to test the resilience of a network and assess the systemic importance of the components in the network. Among the prominent quantitative network methodologies using market data, the most widely applied models are the Granger-causality network by Billio et al. (2012) and the vector-autoregressive (VAR) model proposed by Diebold and Yilmaz (2009, 2012, 2014).

The core method used in our study is the seminal approach proposed by Diebold and Yilmaz (2009) and improved by their later works (Diebold and Yilmaz, 2012, 2014), which explicitly measures the interdependence among the variables based on the vector autoregressive (VAR) model (Sims, 1980) and the generalized forecast error variance decomposition method (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998). This approach generalizes the univariate autoregressive model by incorporating multivariate time series to enable a more flexible and rich structure, without having to specify in advance which variables are endogenous or exogenous. Given no prior information on the underlying relationships between the series of a system, all variables are considered endogenous and estimated in a VAR model (Sims, 1980).

The initial model of Diebold and Yilmaz (2009) has a methodological limitation of relying on the ordering of variables for the variance decomposition, arising from its adoption of the Cholesky factor identification of VARs. Diebold and Yilmaz (2012) tackle this problem by replacing the Cholesky factorization by the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), to make variance decomposition invariant to ordering. Diebold and Yilmaz (2014) further refine the basic VAR model of Diebold and Yilmaz (2009) to set up a network analysis. Their model has been widely applied in empirical studies to investigate the interconnectedness between stock market returns and oil shocks (Zhang, 2017), international commodity markets (Zhang and Broadstock, 2018), energy markets (Ji et al., 2018c; Zhang et al., 2018), housing markets (Zhang and Fan, 2018), stock markets (Wu et al., 2019), etc.

The lag length for the VAR model in this study is selected by minimizing the value of the Bayesian information criteria, as by construction it imposes a higher penalization for the model with an intricate parametrization compared to the Akaike information criterion. For a K-variable VAR(p) model, it can be expressed as:

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{A}_1 y_{t-1} + \boldsymbol{A}_2 y_{t-2} + \cdots + \boldsymbol{A}_p y_{t-p} + \boldsymbol{u}_t \tag{4.3}$$

where $\mathbf{y}$ is a $(\mathrm{K} \times 1)$ vector of variables at time t; $\boldsymbol{c}$ and $\boldsymbol{u}$ are $(\mathrm{k} \times 1)$ vectors of constants and error terms at time t, respectively; $\mathbf{A}$s are $(\mathrm{K} \times \mathrm{K})$ matrices of coefficients. A more compact version for the VAR model is:

$$\boldsymbol{Y}_t = \boldsymbol{C} + \boldsymbol{A} Y_{t-1} + \boldsymbol{U}_t \tag{4.4}$$

Upon estimating the VAR model, the forecast error variance decomposition (FEVD) approach can then be applied to the estimated VAR to find out how much one variable i can help in explaining the variation of another variable j, or how long these effects require to take place. In practice, FEVD usually adopts the Cholesky decomposition, and the results are therefore sensitive to the ordering of the variables. Instead of changing the order of variables to check the robustness of the FEVD results, we adopt the generalized decomposition method to circumvent the issue of ordering in the standard VAR analysis, following the suggestion of Diebold and Yilmaz (2014). After estimating the VAR model, the mean squared error of the H-step forecast of variable y_i is:

$$MSE[y_{i,t}(H)] = \sum_{j=0}^{H-1} \sum_{k=1}^{K} (e_i' \Theta_j e_k)^2 \tag{4.5}$$

where e_i is the ith column of I_k, whose ith element equals one or zero otherwise; $\Theta_j = \Phi_j P$, where P is a lower triangular matrix through a Cholesky decomposition of the variance covariance matrix $\Omega_u = E(u_t u_t^{'})$, and $\Phi_j = JA^j J^{'}$, with $J = [\mathrm{I}_k, 0, \dots, 0]$. In this study, we follow Diebold and Yilmaz (2014) and Zhang (2017) and adopt MSE to conduct the generalized variance decomposition. It is worth mentioning that besides MSE, other alternatives are also possible, such as MAPE, RMSE, RMSP and MAD (Witt and Witt, 1992), which we hope to explore in future work.

The contribution of the *k*th variable to the *i*th variable, based on the H-period-ahead generalized variance decomposition, is specified as:

$$\varphi_{ik,H}^{g} = \frac{\sigma_{kk}^{-1} \sum_{j=0}^{H-1} (e_i^{'} \Phi_j \Sigma_u e_k)^2}{MSE[y_{i,t}(H)]} \tag{4.6}$$

where σ_{kk} is the standard deviation of the error term of the *k*th equation.

Denoting the GFEVD of any two variables as φ_{ij}, which measures how much variable *i* is explained by variable *j*, then a K× K connectedness matrix (for example, Zhang, 2017) can be constructed for a K-variable system. Between any given pair of variables (*i*, *j*), the relative contribution, or net contribution, from variable *j* to *i* can be calculated as $\varphi_{ij} - \varphi_{ji}$, and vice versa. A positive value of the net contribution from *j* to *i* indicates that variable *j* contributes more to than receiving from variable *i*, or in other words, variable *j* is a net contributor to variable *i*. The top net contributor in a system is characterized by making the most net contributions to other variables, meaning that it is the most influential component in the system among all and has the strongest explanatory power of the future variations of all the other variables. It therefore can be used to forecast the market dynamics.

To find how the whole system is interconnected, or put differently, integrated, Diebold and Yilmaz (2014) define a measure called total connectedness, which essentially is the aggregation of pairwise connectedness excluding self-contributions. In the K by K connectedness matrix for a K-variable system, it is calculated as the sum of all off-diagonal elements divided by the total number of variables in the system:

$$\mathrm{s} = \frac{1}{K}\sum_{j=1}^{K}\sum_{i=1}^{K}\varphi_{ij,H}\,, for, i \neq j \tag{4.7}$$

By construction, diagonal elements of the connectedness matrix show self-contributions (when i = j) and are excluded when calculating the total connectedness. The value of s ranges between zero and one, respectively indicating that the system components are all mutually independent or perfectly dependent on each other. We follow Zhang (2017) to set H=10, as the connectedness matrix may change when H is too small, while converging quickly to a stable value when H becomes higher, as discussed in Diebold and Yilmaz (2009) and Zhang (2017).

Diebold and Yilmaz (2014) also introduce three additional measures:

$$\mathrm{From}_i = \sum_{j=1}^{K}\varphi_{ij}\,, for, i \neq j \tag{4.8}$$

$$\mathrm{To}_i = \sum_{j=1}^{K}\varphi_{ji}\,, for, i \neq j \tag{4.9}$$

$$\mathrm{Net}_i = \mathrm{To}_i - \mathrm{From}_i \tag{4.10}$$

where From_i describes how much one variable i gains from all the others in the system; To_i describes how much variables i contributes to the system; Net_i calculates this variable's net contribution to the system, which can be positive or negative, depending on whether it is a net contributor or net receiver. To further account for the time variation in the system interconnectedness, we follow Diebold and Yilmaz (2009) to use the rolling-window analysis to render a time-varying picture of the intra-system connectedness, which estimates the VAR models recursively using overlapping subsamples (windows). The window size in this study is selected as a quarter of the total number of observations.

4.3.2 Accounting for the global common factors

A central task of this study is to explore the intrinsic integration among major East and Southeast Asian stock markets, which does not depend on the influences of the global stock market. The dynamics in the world stock market inevitably exert significant influences on local stock markets, especially during the progress of reducing barriers to foreign investment and liberalizing stock markets in recent years, or in an episode of risk contagion arising from a systemic event. This therefore gives rise to concerns that correlation-based approaches may generate biased conclusions on equity market integration, as returns used for calculating cross-market correlations encompass influences from both global and non-global sources. Pukthuanthong and Roll (2009) and Carrieri et al. (2007) suggest the impropriety of directly inferring the real level of financial market integration by market-wide index return correlations, as there are cases where perfectly integrated markets can exhibit weak correlation in the presence of multiple global sources of return volatility and differing levels of sensitivities of markets to them.

Our filtering method is inspired by the international capital asset pricing model (ICAPM). Arouri and Foulquier (2012) introduce an augmented international asset pricing model to account for partial financial market segmentation and to reflect local risk that is not internationally diversifiable. The authors find that most emerging markets become more integrated as a result of liberalization and reforms. Abid et al. (2014) and Boubakri and Guillaumin (2015) focus on South Asia and East Asia stock market integration, respectively, using the international capital asset pricing model. The ICAPM has also been discussed in, for example, Vithessonthi and Kumarasinghe (2016) and Yao et al. (2018).

To investigate whether the ASEAN5+4 stock markets are still strongly linked in the absence of common driving forces from the global stock market, we attempt to filter out the influences of the world stock market dynamics on local stock market returns, based on a simple market model expressed as:

$$y_{i,t} = \alpha_i + \beta_{i.t} y_{w,t} + \varepsilon_{i,t} \tag{4.11}$$

where $y_{i,t}$ denotes the return of market i at time t; α_i is the constant; $y_{w,t}$ is the return of the world stock market at time t with a coefficient $\beta_{i.t}$; $\varepsilon_{i,t}$ is the error term, showing the part of the ith market's idiosyncratic component from the total return at time t, which is attributed to factors other than common global impacts. These filtered returns are then used to investigate the interrelationships among local stock market returns, free from the disturbances of common global stock market impacts.

4.4 Data

We study a group of 11 major stock markets in East and Southeast Asia, including five stock markets in the ASEAN countries (hereinafter referred to as ASEAN5, which are Indonesia, Malaysia, the Philippines, Singapore and Thailand), and four stock markets in the East Asia region, including mainland China, China Hong Kong, Japan and South Korea[19]. Weekly stock market price indices for these ASEAN5+4 stock markets and a world aggregate market are collected from Thomson Reuters Datastream, denominated in US dollars. Returns are calculated as the log difference of weekly stock market price indices, which by construction are the growth rate of stock market price indices. While bigger stock markets with higher market values are usually considered to exert more influences on the dynamics of the regional stock market, using this construction of stock market returns allows us to equally weigh the individual stock markets in this region, so as to evade the direct impacts of their relative sizes on analysing regional stock market co-movements.

The sample period is selected to be between 23 June 1999 and 26 June 2019, with in total 1044 observations for each stock market. We select 2002 as the starting year, which avoids the structural break caused by the Asian financial crisis starting from July 1997 that gripped not only much of Asia but also the broader global economy due to financial contagion, as well as the potential substantial influences of several wide-ranging political and economic reforms implemented in the ASEAN region during the crisis. The causes and effects of the 1997-98 crisis have been examined by numerous studies, which this study does not intend to discuss.

[19] For brevity, the mainland China and China's Hong Kong stock markets are respectively referred to as "China" and "Hong Kong" hereinafter in the main text, tables and figures.

Our sample period still covers some recent extreme systemic events, including the prominent 2008 global financial crisis, its aftermath and the European sovereign debt crisis starting from the end of 2009.

The descriptive statistics of stock market returns in the nine local stock markets and the world stock market are shown in Table 4.1. Over the sample period, Thailand has the highest mean return among all markets, followed by South Korea and then the Philippines. Japan shows the lowest mean return, remarkably lower than its follower China. They are also the only two in the sample with lower mean returns than the world market's aggregate level. Comparing the ASEAN5 group to the East Asia group, the average return of ASEAN5 stock markets is higher. Within the ASEAN5 group, Singapore has the lowest mean return, while Thailand has the highest. Among the East Asian stock markets, Japan has the lowest while South Korea has the highest mean returns, respectively.

Table 4.1 Descriptive statistics of stock market returns

	Mean	Median	Maximum	Minimum	Std.	Skewness	Kurtosis	Jarque-Bera
CHINA	0.049	0.096	13.874	-24.906	3.408	-0.414	6.911	695.255
HONGKONG	0.079	0.266	14.829	-14.437	2.988	-0.426	5.722	353.995
INDONESIA	0.076	0.282	21.790	-32.526	4.319	-0.828	10.734	2721.240
JAPAN	0.023	0.139	12.984	-14.685	2.649	-0.271	5.006	187.714
KOREA	0.089	0.314	30.656	-26.901	4.224	-0.305	9.408	1802.453
MALAYSIA	0.076	0.174	11.141	-17.964	2.368	-0.575	8.107	1192.176
PHILIPPINES	0.080	0.139	24.596	-15.212	3.079	0.192	8.906	1523.848
SINGAPORE	0.066	0.124	14.346	-16.944	2.609	-0.308	7.553	918.082
THAILAND	0.120	0.285	19.372	-21.414	3.615	-0.393	6.265	490.526
WORLD	0.062	0.261	8.200	-17.894	2.288	-0.938	8.178	1319.273

Note: Std. denotes standard deviation. Jarque-Bera denotes the statistics of Jarque-Bera test for normality. *** denotes the 1% significance level.

Considering market volatility, the top three markets with the highest levels of standard deviation are Indonesia, South Korea and Thailand, implying more volatility in these three markets than in others over the full sample period. The standard deviation of Malaysia is the lowest, followed by Japan and Hong Kong, notwithstanding all higher than the world market, indicating that these markets are systematically more volatile than the global stock market. The average volatility of the ASEAN5 markets is lower than that of the East Asian markets, indicating that the latter are generally more volatile than the former. Among the ASEAN5 markets, Indonesia has the highest volatility, while Malaysia the lowest. Within the East Asian group, South Korean and Japanese markets are the most and least volatile ones, respectively.

We then plot each stock market's return series over the sample period in Figure 4.1. The most volatile periods in all markets are seen during the 2008 financial crisis period. Based on this observation and to address the significant impacts of the 2008 financial crisis, the whole sample is divided into pre- and post-crisis periods by the date 10 September 2008, as the Lehman Brothers filed its bankruptcy protection on 15 September 2008, which triggered the largest one-day drop in the Dow Jones Industrial Average (4.5%) since the 911 attacks in 2001 and unfolded financial contagion across the US and global markets. Using weekly data, the sample dates before and after the Lehman Brothers event are 10 and 17 of September 2008, respectively. We therefore select the first date to divide the sample into two subsamples.

4.4.1 Graph theory and the minimum spanning tree

Deeley (2016) uses graph theory to illustrate within-system dependencies via a simple mapping strategy. We adopt the minimum spanning tree (MST) based on graph theory to provide graphic evidence on the network structure of the East and Southeast Asian stock markets, following the extant literature (Mantegna, 1999; Onnela et al., 2004; Ji and Fan, 2016; Wu et al., 2019). As a classic tree derived from graph theory, the minimum spanning tree has the advance of extracting the most important relationships among all variables in the system, while expressing it in a simplest way that is easy to visualize and identify the most crucial nodes and relationships. By construction, it chooses only the *K*-1 strongest links among all *K*(*K*-1)/2 possible links for N vertices in a system, to construct a network with possibly the shortest path to connect all these vertices, thus much reducing the complexity of constructing the network.

The construction of the MST is based on the calculation of pairwise correlations. Denote the correlation between two variables *i* and *j* as ρ_{ij}, which is calculated by:

$$\rho_{ij}^{T} = \frac{\sum_{t=1}^{T}(r_{i,t}-\bar{r}_i)(r_{j,t}-\bar{r}_j)}{\sqrt{\sum_{t=1}^{T}(r_{i,t}-\bar{r}_i)^2 \sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^2}} \tag{4.1}$$

The correlation coefficient cannot be applied to measure distance, as it violates the three axioms of the Euclidean distance (Gower, 1966). Instead, the correlation coefficient can be converted to a distance variable using a simple distance function:

$$d_{ij} = \mathrm{f}\left(\rho_{ij}\right) = \sqrt{2(1-\rho_{ij}^{T})} \tag{4.2}$$

where d_{ij} denotes the distance between nodes i and j, which satisfies the three axioms of the Euclidean distance, including: (1) $d_{ij} = 0$, if and only if $i =$ j; (2) $d_{ij} = d_{ji}$; and (3) $d_{ij} \leq d_{ik} + d_{kj}$. A smaller value of d_{ij} implies that the two stock markets are more correlated and compact.

The pairwise distances then form a distance matrix, which is used to connect all stock markets in an undirected network graph G. An MST can then be constructed to link together all nodes (stock markets) in the graph G with minimum possible total edge weight (Mantegna and Stanley, 2000). In this paper, the MST problem is solved by the Prim's algorithm, which can be found in Prim (1957) and Dijkstra (1959).

4.5 Empirical analysis

4.5.1 Correlation analysis

We first construct a correlation matrix by Pearson's rank correlation coefficients for the ASEAN5+4 stock market returns using equation (4.1), without filtering the world stock market effects. Figure 4.2 uses heat maps to visualize pairwise dependences during the full sample and two sub-periods, with lighter colours indicating lower levels of correlation or darker colours otherwise. Diagonal elements representing self-correlation equalling one are not shown here.

Over the full sample period, it can be spotted that the colour of China is on average the lightest, reflecting the lowest level of aggregated correlation with all the other markets. By contrast, much darker colours are seen for Singapore, Hong Kong and South Korea, indicating their high correlations with other markets. The highest pairwise correlations are seen exactly among them. Consistent with China's lightest colour, it appears in top three lowest correlations with Japan, South Korea, and Thailand/Indonesia (with equal magnitudes). The average correlation of the East Asia group is lower than that of the ASEAN5. Same rankings are seen in the subsample results. Each market's aggregate correlation with all the others increases substantially by over

40% during the post-crisis period, with China, Malaysia and Indonesia increasing the most, causing a substantial increase of the system's aggregate correlation during this period.

The correlation results after filtering the effects of the world stock market are reported in the heat maps in Figure 4.3. Singapore and Hong Kong are still among the top three most correlated markets, and their correlation is always the highest, irrespective of sample period or data type selected. South Korea is no longer among the top three, replaced by Thailand and Indonesia in each sub-period, respectively. The least correlated market is no longer China but Japan over the full sample period and the post-crisis period. The filtering process not only changes these rankings, but also systematically and remarkably reduces the magnitudes of pairwise correlations, leading to the aggregate level of correlation declined by over 45% in each period.

This finding may indicate that the previously high correlations computed by non-filtered returns is largely attributable to the common influences from the world stock market. Two seemingly highly correlated markets may not actually be that much correlated, if we manage to remove the influences from the global stock market dynamics, especially when both markets are commonly susceptible to these global factors. Furthermore, the filtering process leads the aggregate correlation for the post-crisis period to drop by 47.8%, slightly more than for the pre-crisis period (46.7%), possibly implying that the post-crisis markets seem more susceptible to global stock market influences.

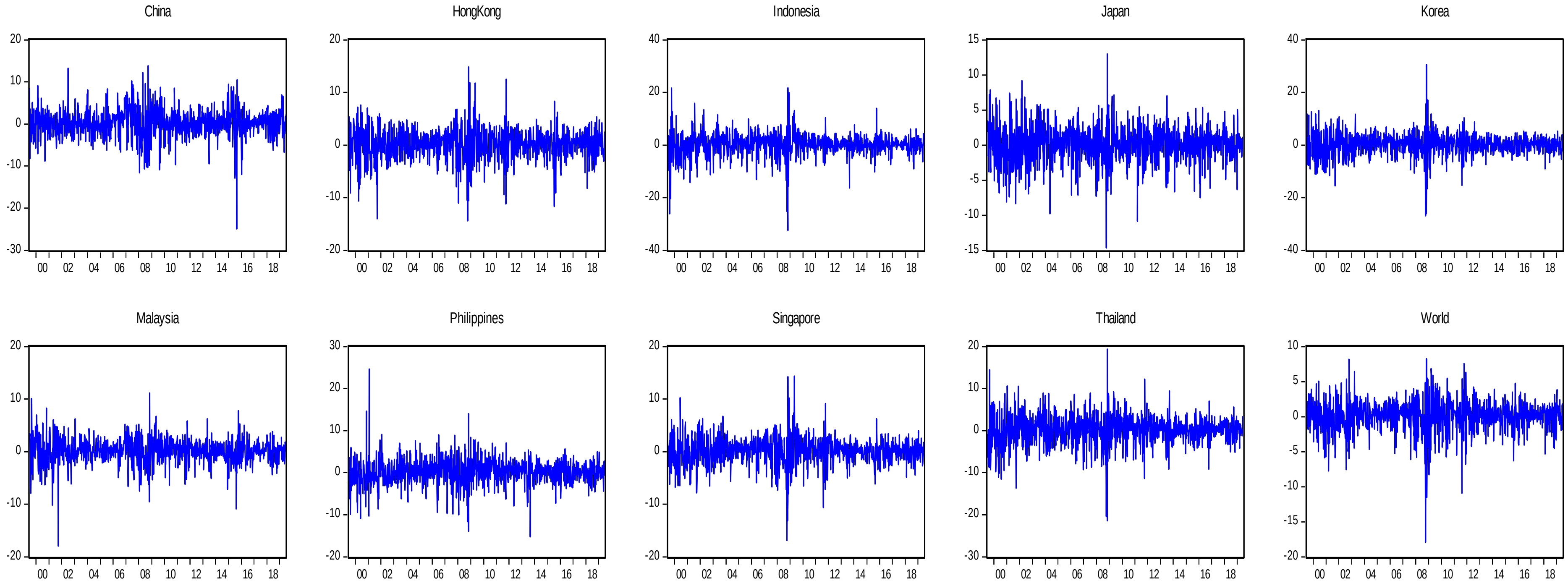


Figure 4.1(a) Time series plots of return series

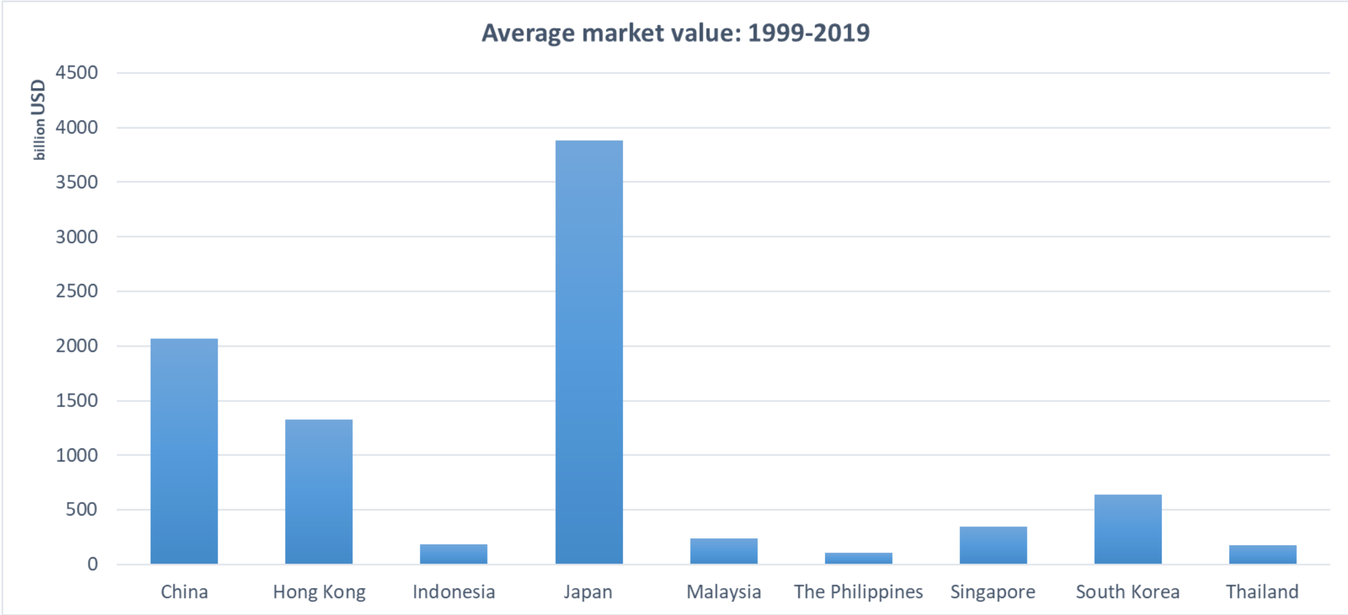
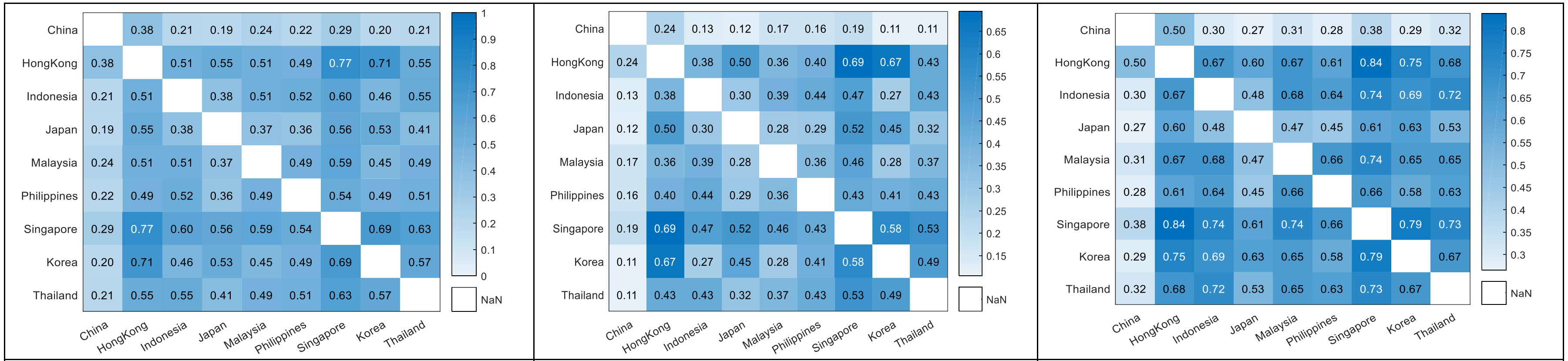


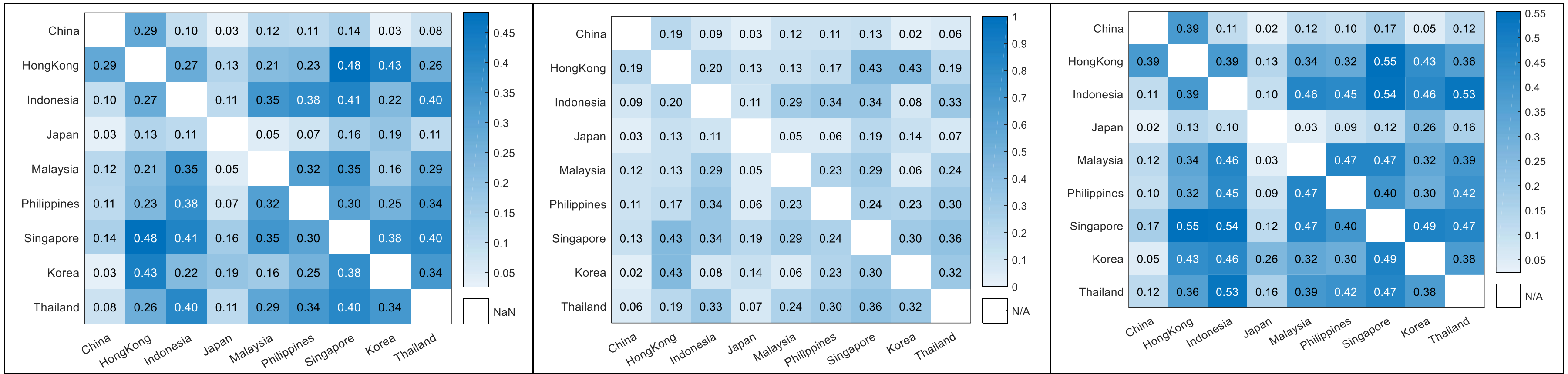
Figure 4.1(b) Average market value

Figure 4.1 Time series plots of return series and average market value



(a) Full sample (b) Pre-crisis period (c) Post-crisis period

Figure 4.2 Correlation heatmap of raw returns for full sample, pre- and post-crisis periods



(a) Full sample (b) Pre-crisis period (c) Post-crisis period

Figure 4.3 Correlation heatmap after filtering the world stock market

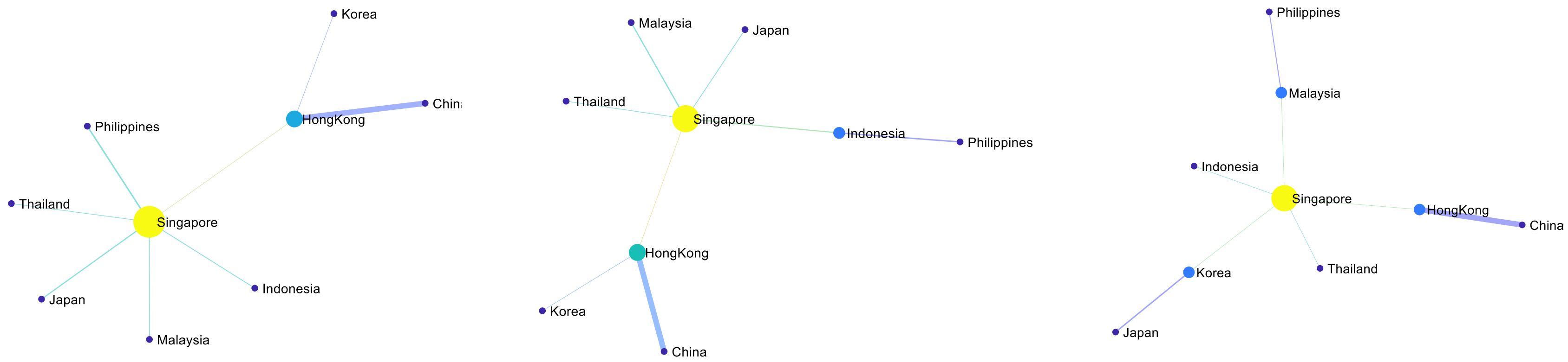
4.5.2 MST results

Given the correlation matrices, we proceed to calculate the distance matrix for all pairwise markets using equation (4.2) and construct an MST for the system. Figure 4.4 shows the three trees presenting the full sample and two sub-periods, respectively, based on raw returns. Considering the significant impacts of the global stock market factors, we examine how the MSTs tend to change after filtering the effects of the world stock market. The results are shown in Figure 4.5. The stock market with the highest degree centrality is highlighted as the most central node, where the degree centrality is defined as the number of edges incident to a given node. Also, the shorter the pairwise distance is, the thinner is the edge between them.

Seen in Figure 4.4(a), Singapore and Hong Kong are the two most central markets, each connecting together markets in its own region (except Japan). Clustering effects are therefore observed in both ASEAN5 and East Asia groups. The link between Singapore and Hong Kong is also the strongest, evidenced by their thinnest edge. The edges among ASEAN5 markets seem on average thinner than among the East Asian markets, indicating stronger cross-market links in the former region. China appears to be the least central node. Although these findings are consistent with the correlation results, disparities are, for example, South Korea which is among the top three most correlated appears to be not central in the MST. Also, the highly correlated Singapore-South Korea over the full sample are not directly linked in the MST.

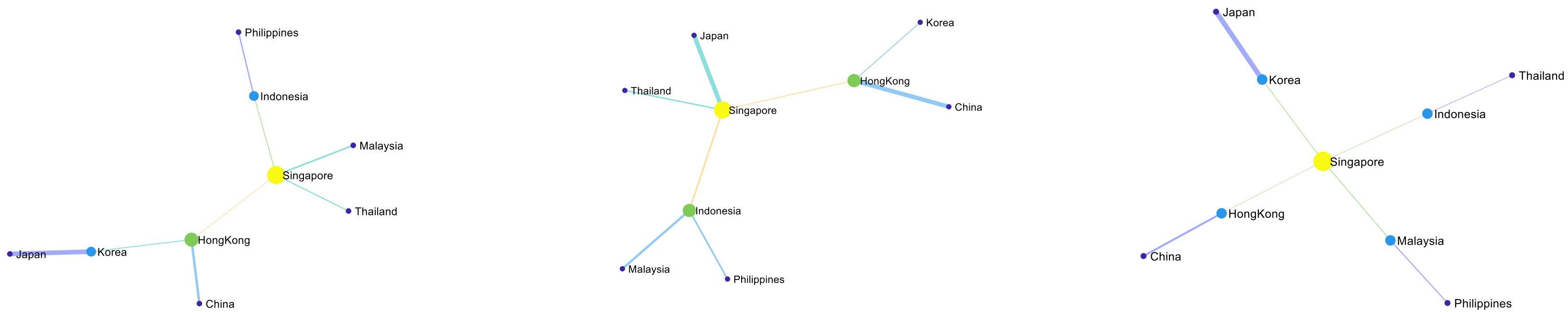
The main findings for the pre-crisis period (See Figure 4.4(b)) are almost the same as for the full sample. Comparing Figures 4.4(b) and 4.4(c), the post-crisis MST maintains some of the pre-crisis characteristics, but meanwhile presents substantial changes. The whole network seems more interconnected and centralized. Singapore remains central but is decoupled from Japan and the Philippines (as opposed to the full sample tree), despite their high post-crisis correlations. This implies that some other post-crisis correlations increase to a greater extent than those pairs, making them less important in the post-crisis MST. Rather than only Hong Kong in the pre-crisis period, new sub-central nodes emerge in this post-crisis tree.

Seen in Figures 4.5(a)-(c), after filtering the world stock market effects, the whole network is less compact but more stretching out over the full sample. The central role of Singapore is maintained but lessened. The filtering process causes the pre-crisis tree to change from a two-centre to a three-centre structure, as Indonesia and Hong Kong appear to be important, each linking to three markets. For the post-crisis period, the filtering process changes the location of Thailand, and the weakest link is no longer between Hong Kong and China, but between Japan and South Korea instead.



(a) Full sample (b) Pre-crisis period (c) Post-crisis period

Figure 4.4 MST for raw returns



(a) Full sample (b) Pre-crisis period (c) Post-crisis period

Figure 4.5 MST after filtering the world stock market effects

4.5.3 VAR-based results

To verify the graphic evidence shown by the MST, we opt for a multivariate time series approach proposed by Diebold and Yilmaz (2014) to further test the interconnectedness among the ASEAN5+4 stock markets, accompanied by a rolling-window approach to capture the dynamics of the cross-market relationships, following the extant literature (among others, Zhang, 2017; Zhang et al., 2018; Wu et al., 2019). We first fit the ASEAN5+4 returns into a VAR model, and then obtain a connectedness matrix by the GFEVD method, which shows the overall connectedness in the system, as well as each market's gains and contributions to others. To account for the impacts of the world stock market dynamics on the system's interconnectedness, we compare the results generated by both raw and filtered returns, respectively shown in Panels I and II of Table 4.2.

Interconnectedness by raw returns

Seen in Panel I of Table 4.2, the overall connectedness in the system without filtering the world stock market effects is quite high, as high as 63.42% over the full sample, calculated as the average of the values of all non-diagonal elements. This indicates that the ASEAN5+4 stock markets are highly interconnected using raw returns. From a financial stability perspective, the implication is that financial contagion is more likely to arise, as systemic risk and information can easily spread across the East and Southeast Asian markets due to their high interconnectedness (Wu et al., 2019).

Table 4.2 Connectedness matrices before and after filtering the world stock market effects

Panel I. Connectedness matrix for raw returns

	China	Hong Kong	Indonesia	Japan	Malaysia	Philippines	Singapore	Korea	Thailand	From
China	65.51%	10.17%	3.10%	2.48%	3.73%	3.49%	5.91%	2.71%	2.90%	34.49%
Hong Kong	4.20%	27.66%	7.34%	8.10%	7.18%	6.83%	16.64%	13.87%	8.19%	72.34%
Indonesia	1.60%	9.15%	34.75%	4.99%	8.98%	9.45%	12.78%	7.85%	10.44%	65.25%
Japan	1.56%	11.57%	5.91%	39.64%	5.21%	5.34%	12.55%	11.30%	6.91%	60.36%
Malaysia	1.91%	9.71%	9.30%	4.91%	36.28%	8.36%	13.29%	7.56%	8.67%	63.72%
Philippines	1.74%	9.03%	9.87%	5.00%	8.44%	36.17%	11.03%	8.70%	10.02%	63.83%
Singapore	2.13%	15.58%	9.09%	8.22%	9.05%	7.50%	26.07%	12.19%	10.17%	73.93%
Korea	1.21%	15.25%	6.65%	8.77%	6.13%	7.24%	14.46%	30.45%	9.86%	69.55%
Thailand	1.44%	9.80%	9.67%	5.91%	7.82%	8.73%	13.18%	10.71%	32.73%	67.27%
To	15.80%	90.27%	60.93%	48.38%	56.54%	56.93%	99.84%	74.89%	67.16%	63.42%
Net	-18.69%	17.93%	-4.32%	-11.98%	-7.18%	-6.89%	25.91%	5.33%	-0.11%	

Panel II. Connectedness matrix for filtered returns

	China	Hong Kong	Indonesia	Japan	Malaysia	Philippines	Singapore	Korea	Thailand	From
China	85.96%	7.75%	1.03%	0.15%	1.26%	1.28%	1.79%	0.11%	0.68%	14.04%
Hong Kong	4.85%	55.28%	5.43%	0.87%	2.79%	3.37%	13.23%	9.89%	4.29%	44.72%
Indonesia	0.90%	4.14%	56.90%	0.58%	7.15%	8.36%	9.88%	3.21%	8.87%	43.10%
Japan	0.40%	1.54%	2.43%	87.39%	0.25%	1.08%	2.57%	2.86%	1.49%	12.61%
Malaysia	0.89%	3.23%	8.08%	0.12%	64.59%	6.58%	8.83%	1.98%	5.70%	35.41%
Philippines	0.79%	3.62%	9.07%	0.35%	6.20%	61.85%	6.01%	4.18%	7.93%	38.15%
Singapore	1.07%	11.83%	8.75%	1.35%	6.53%	4.86%	50.05%	7.28%	8.28%	49.95%
Korea	0.11%	10.91%	4.17%	1.87%	1.94%	4.20%	8.67%	60.62%	7.52%	39.38%
Thailand	0.58%	3.96%	8.93%	0.70%	5.08%	7.15%	9.48%	6.69%	57.43%	42.57%
To	9.59%	46.98%	47.90%	5.99%	31.18%	36.87%	60.46%	36.20%	44.76%	35.55%
Net	-4.45%	2.26%	4.79%	-6.62%	-4.23%	-1.28%	10.51%	-3.18%	2.19%	

Note: "From" denotes the aggregation of horizontal elements for each variable in the matrix, while "To" is the aggregation of vertical elements for each variable, both excluding the diagonal elements which represent self-connectedness. "Net" is calculated as the difference between the values of "To" and "From", measuring the net contribution made by this variable to the whole system.

To gauge each individual market's susceptibility and contribution to the dynamics of the whole system, the last column "From" and the row "To" are respectively calculated by equations (4.8) and (4.9) to present the levels of each. While there is an upper bound for the measure "From" (100% maximum variation for any variable), the magnitude of "To" can exceed 100% (in theory, it can go to a maximum value of K).

The figures of "From" are generally above 60%, ranging from 60.36% to 72.34%. This indicates that most of the stock markets gain substantial information from the system, except China only receiving 34.49% from the system. The top receivers are Singapore, Hong Kong and South Korea. Compared to "From", the contributions made by each market vary significantly, with the three top receivers also being the top contributors. All markets contribute more than 50% to the system, except China and Japan. Combining these results, China is found to receive and contribute the least, while Singapore is the opposite, which are consistent with the non-filtered graphic evidence of the MST.

The last row "Net", computed as the difference between the magnitudes of "To" and "From", measures the net contribution made by a market to the whole system. It simultaneously considers each market's contributions and gains, and is therefore more informative and comparable to the MST findings, relative to either "From" or "To". Most markets have negative values of "Net", indicating that they receive more than they contribute over the sample period, and are thus net receivers. Among them, China "net" receives the most from the system. There are only three net contributors to the system, Singapore, Hong Kong and South Korea. These results, again, correspond to the MST findings.

Pairwise connections are plotted in Figure 4.6 to visualize the connectedness and interaction among all markets. The nine stock markets in the system are connected by 36 edges, arranged radially around a circle and represented by nodes on the outer part of the circular layout. Directed arrows are drawn to show pairwise relationships. If market *i* explains more than it is explained by market *j* ($i \neq j$), an outward edge (arrow) is drawn pointing from *i* towards *j*, or otherwise an inward edge is drawn, enabling us to easily see the overall interactions among all nodes. Singapore as the top net contributor is highlighted by a red diamond. With eight outgoing edges and "net" contributing to all the other markets, it should be considered the most influential market in the system. China, by contrast, is highlighted by a blue square. It net receives from all the others with zero outward edges, affected by all while influencing none.

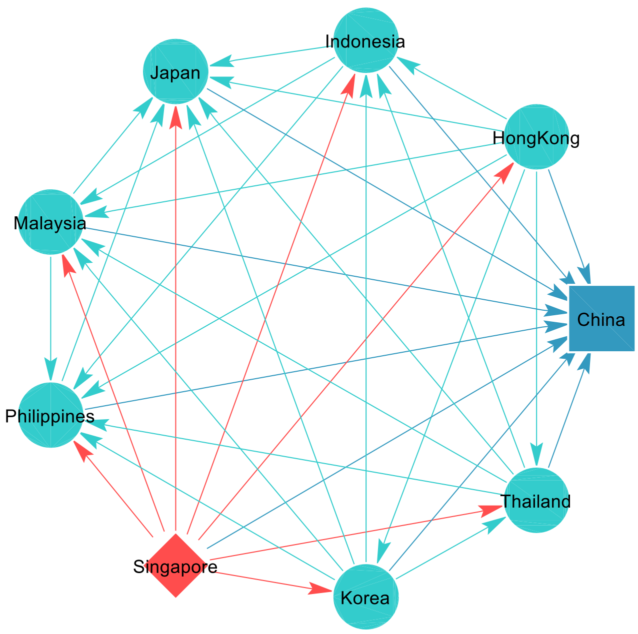


Figure 4.6 Full-sample pairwise connectedness for raw returns

A chord diagram is also depicted to visualise the weighted interrelationships among these markets. In the diagram, nodes (markets) are arranged radially along a circle, with the relationships between markets connected to each other through arcs. The outer part of the circular layout represents each market's importance in the network based on the magnitude of the "Net" measure. Values are also assigned to each connection, which are represented proportionally by the size of each arc. Figure 4.7 showcases the importance of Singapore by both its largest shadow on the outer layer and its thick arcs connecting to other nodes.

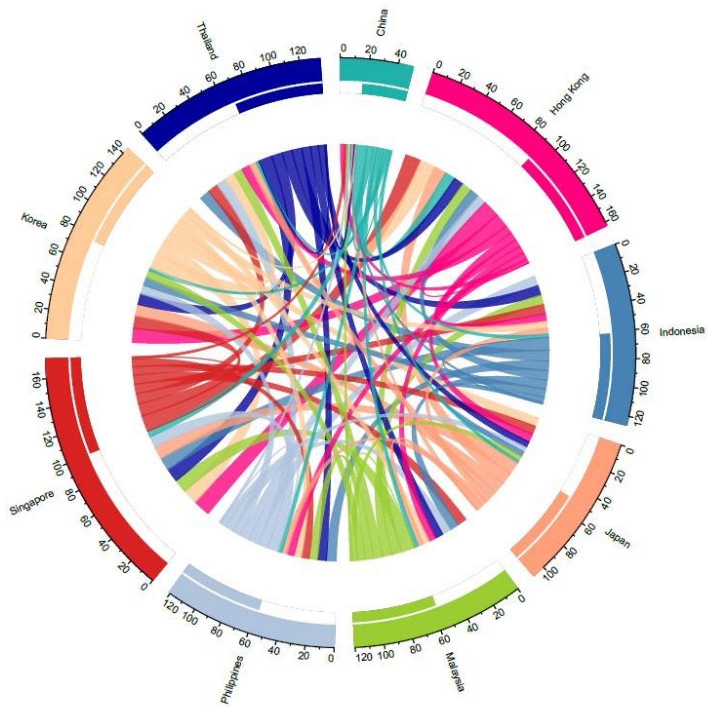


Figure 4.7 Chord chart of the connectedness matrix for raw returns

These results reflect the average level of connectedness in the system over the full sample period of 20 years, rendering a static snapshot of the connections among the ASEAN5+4 stock markets. The complex and multifaceted equity markets, however, are prone to unpredictable exogenous shocks, evolving market practices and sentiments, and on-going legal and institutional updates from both domestic and international sources. We well expect that interconnectedness among these stock markets tends to change over time. To depict the dynamics of how the intra-system connectedness evolves, we apply a simple rolling-window approach to the VAR model, following the literature (Diebold and Yilmaz, 2009, 2012; Zhang, 2017; Ji et al., 2018c; Zhang et al., 2018).

There, however, has been no consensus on window length selection (Ji and Fan, 2016). With in total 1044 observations from 23 June 1999 to 26 June 2019, we select a quarter of this number (which is 261 weeks, approximately five years) as our window size, which can well reflect the characteristics of time series data, but is neither too long nor too short to render too smooth or noisy data that may affect the robustness of our results. Moving along the time scale with one window step length, there are totally 784 windows to be recursively estimated. The VAR model is estimated for each window, implying that the full sample connectedness should not be simply calculated as the average of the connectedness of rolling windows, although they are mutually comparable (Zhang, 2017).

A rolling-window version of connectedness is shown in Figure 4.8. The total connectedness among the ASEAN5+4 stock markets of each window is plotted corresponding to the end of that particular window. The interconnectedness of the whole system clearly exhibits a time-varying trend. The lowest point, which is less than 50%, is seen at the beginning of the timeline corresponding to the window ending in 2004. It then climbs up steadily to the around 72% when the window ends in early 2008, and levels until the third quarter of 2008, when it starts rising sharply as the global financial crisis unfolds. The connectedness maintains at its peak (around

79%) from the beginning of 2009 to the middle of 2013, covering the global financial crisis and its aftermath, as well as the European sovereign debt crisis. After that, systemic interconnectedness shows a declining trend and decreases to around 70% in early 2017 and levels off till the end of the sample period.

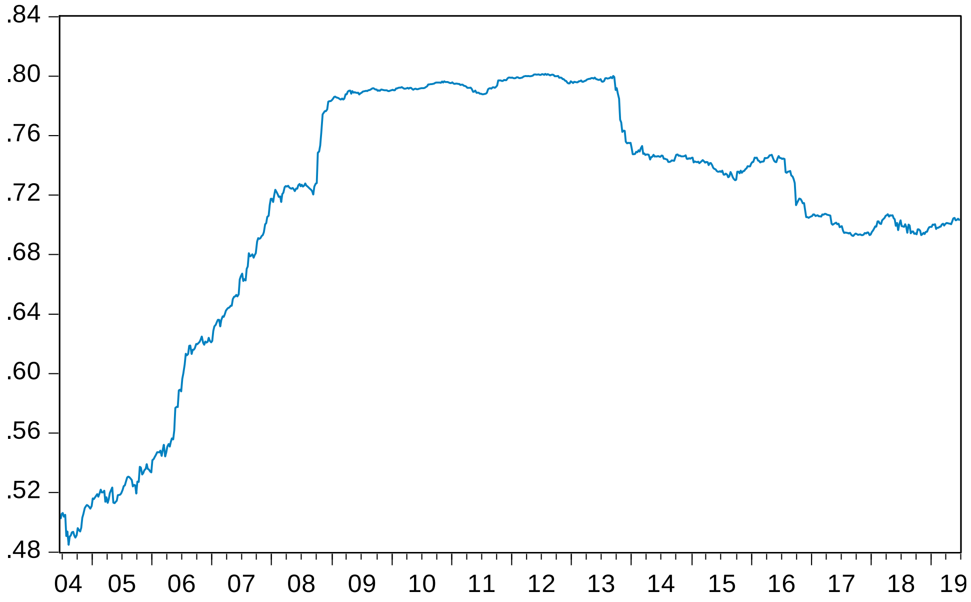


Figure 4.8 Rolling-window total connectedness

Interconnectedness by filtered returns

Substantial changes in the full sample connectedness matrix are seen after filtering the world stock market effects, as shown in Panel II, Table 4.2. Most notably, the full-sample total connectedness in the system decreases from 63.42% before filtering to 35.55% after filtering the world stock market effects, dropping by 44%. This indicates that the previously estimated high interconnectedness among ASEAN5+4 stock markets seems to be largely driven by the global market influences that all markets are commonly exposed to. After filtering out the contribution by the world stock market impacts, cross-market interconnection therefore significantly decreases.

Each market's gains from and contributions to others decrease remarkably. The top three receivers are Singapore, Hong Kong and Indonesia, who are also the top three contributors, albeit different rankings. The values of "Net" show that Singapore, Indonesia, Hong Kong and Thailand are four net contributors. Interestingly, Indonesia and Thailand, considered as net receivers when using non-filtered data, become net contributors. Although in both cases Singapore and Hong Kong are recognized as net contributors, their net contributions drop substantially in magnitude after the filtering, especially Hong Kong. Considering which market receives and contributes the least, China is replaced by Japan using filtered data. These results, again, correspond to our findings from the MST analysis. The implication is that the ASEAN5+4 stock markets are actually not that highly prone to information spillovers from each other, after removing the component of returns contributed by their common susceptibility to the global market information spillovers. The full sample pairwise connections using filtered returns are plotted in Figure 4.9. The most noticeable difference from Figure 4.6 is that Japan becomes the top net receiver and is highlighted as a blue square. Similar to the non-filtering case, a chord diagram is shown in Figure 4.10 to offer an alternative way of data visualization.

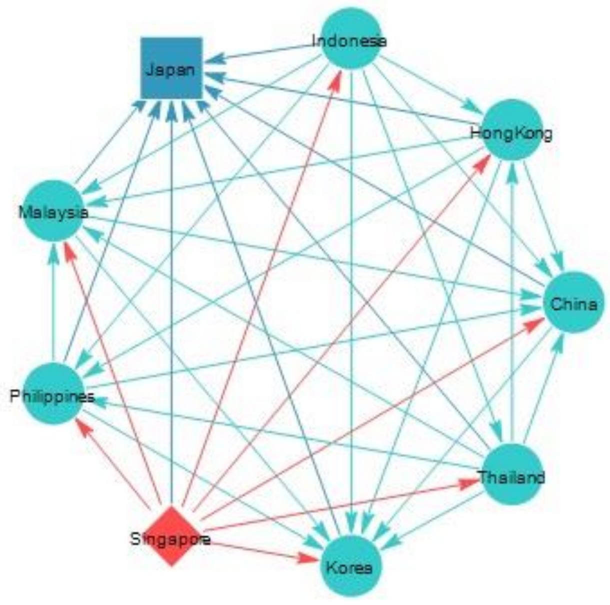


Figure 4.9 Full-sample pairwise connectedness after filtering the world stock market effects

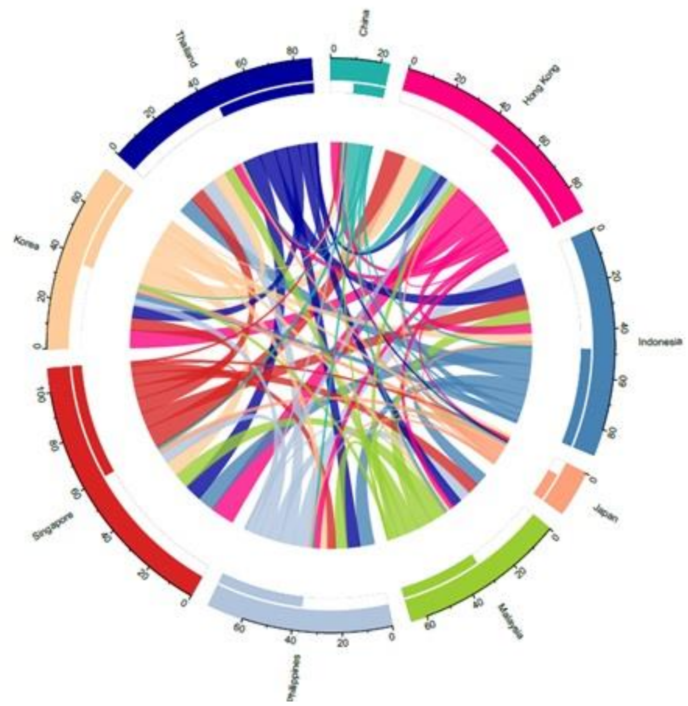


Figure 4.10 Chord chart of the connectedness matrix for filtered returns

A rolling-window version of the filtered connectedness is shown in Figure 4.11, alongside its non-filtered counterpart. These two lines exhibit similar general trends over time, despite different movements at each point of time. It should be noted that although using filtered returns removes the direct influences from the global stock market, regional and local markets are still exposed to information and risk spillovers from the global market, especially with increasing participation of international investors in regional and local markets, who are more susceptible to global market dynamics relative to regional or local investors and adjust their investment behaviour accordingly. The global influences on local markets are thus by no means eliminated, but rather can indirectly drive the co-movement among local markets.

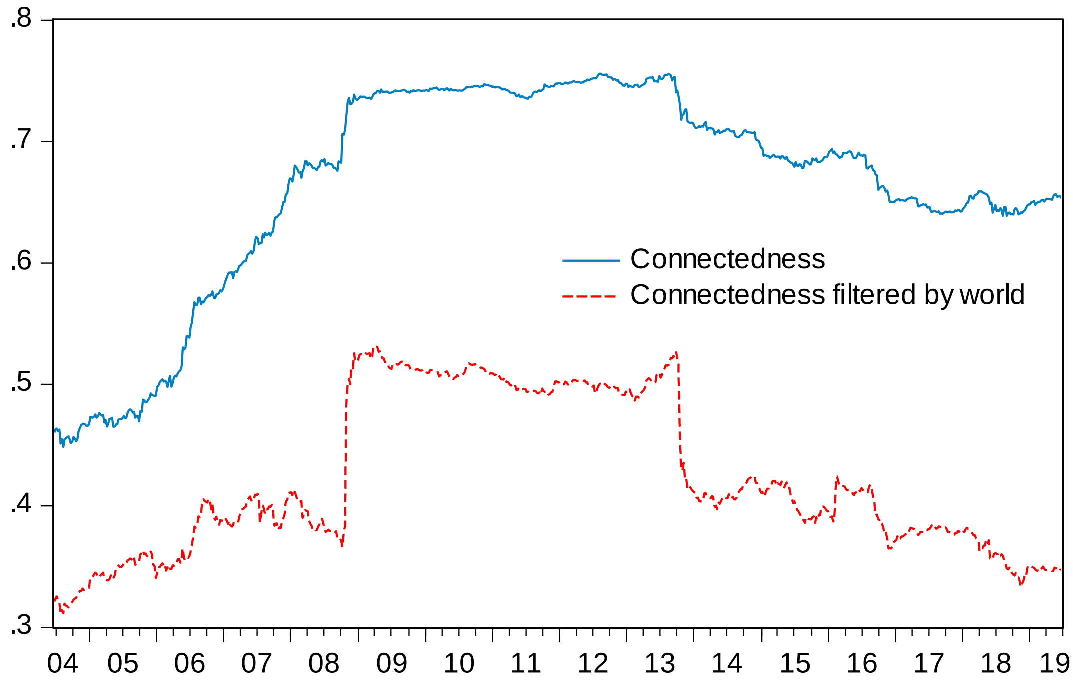


Figure 4.11 Rolling connectedness before and after filtering the world stock market effects

The filtered connectedness, however, is consistently much lower than the non-filtered one over the full sample period. It can be noticed that as time goes by, the gap between their magnitudes tends to enlarge, especially since the 2008 financial crisis. This implies that the bias caused by the failure of filtering out the world stock market influences becomes increasingly pronounced over time, evident by the increasingly overestimated interconnectedness. A plausible explanation can be that connections between the Asian and world markets have been deepened over the past decade (Chowdhury et al., 2019), and local markets are becoming more sensitive to world events (Arouri and Foulquier, 2012), especially since the prominent global crisis. Thinking globally and learning from the experiences of financial contagion, local stock markets are increasingly prudent and alert to information and risk spillovers from foreign markets, especially from neighbour markets or those once closely linked markets, leading to more segmented rather than integrated markets in this region. Failing to rule out the disturbances of the world market dynamics thus tends to harm more the accuracy of estimating the intrinsic cross-market connectedness over time.

Notably, financial market integration has been a long-standing goal of the ASEAN countries, as shown in several official ASEAN documents[20]. To facilitate freer cross-border capital flow and multi-jurisdiction offerings, wide-ranging reforms have been implemented in the ASEAN countries to enhance corporate standards, increase transparency, address the gaps in financial reporting, promote mutual recognition and harmonized disclosure regime, and benchmark with international standards. The ASEAN Common Exchange gateway was created, which is an

[20] For example, the ASEAN Vision 2020 (1997), the Bali Concord II (2003), the ASEAN Economic Community (AEC) 2015 Blueprint (2006), the ACMF (ASEAN Capital Market Forum) Implementation Plan 2015 (2009), etc.

electronic trading link that enables cross-market trading and thus increases the overall trading liquidity (Singh, 2009).

Among the ASEAN5+4 stock markets, however, barriers to financial market integration are far beyond geographic distance between two markets. Capital account restrictions, exchange restrictions and capital control are still believed to play a role, despite a contrasting view of adopting freer policies to deregulate and liberalize markets. There also exist huge disparities in the level of socio-economic and institutional development, trade openness, regulatory and legal environments across these economies (Bekaert and Harvey, 1995; Abid et al., 2014). In the presence of these heterogeneities, the objectives, perceived costs and benefits from integration vary significantly across jurisdictions. Vast differences also exist in terms of tax regimes, market practice, market size and infrastructure, costs, product range, technology investment, liquidity and so on. It is not likely that these markets can achieve parity with each other in these regards. All these factors pose direct and indirect investment barriers to global investors and impede freer flow of capital. To expedite regional integration and translate these initiatives into each government's policy framework, it requires not only alignment of objectives, and also strong political will as well as accommodating, well-tailored and scrupulous plans of implementation.

4.5.4 Robustness test

To test the robustness of our main results based on the VAR approach, we conduct a Granger causality test to find the level of convergence of these stock markets during the full sample and two sub-periods. The results are generally consistent with our main results, suggesting similar patterns of the interconnectedness among the ASEAN5+4 markets using both raw and filtered returns. For brevity, the results are not reported here but are available upon request.

4.6 Conclusions and implications

While evidence in the literature shows that stock markets in Asia have been increasingly integrated in recent years (for example, Chien et al., 2015), we find that the interconnection among the ASEAN5+4 stock markets substantially decreases after we filter out the influences from the global stock market. This indicates that the seemingly high level of cross-market connection is largely caused by the pervasive influences from the global equity market. After the financial crisis, we find that the gap between the levels of interconnectedness estimated by filtered and non-filtered data tends to enlarge over time, implying Asian markets' increasing common exposure to the international market factors.

Our findings therefore answer the question of whether Asian stock markets are really getting more integrated, or whether it is mainly a result of unaccounted information. Or in other words, are the enhanced cross-market linkages simply be driven by common international forces? Our results show that the seemingly high interconnectedness among the local stock markets in East and Southeast Asia is largely caused by common global market factors, consistent with findings in for example, Chen (2018). From a portfolio perspective, failure to filter the systematic factor originated from the global stock market is very likely to lead to overestimation of the intrinsic pairwise correlations in the portfolio. By filtering the effects of the international stock market, we manage to avoid overstating the level of cross-market linkages, and capture the real cross-market correlations not subject to the precondition of pervasive influences from the global market.

Comparing the results from the VAR approach using non-filtered versus filtered data, interconnectedness in the system exhibits similar general trends, but using filtered data consistently and remarkably reduces the level of interconnectedness over the full sample. This implies that failure of filtering out the global market factors can cause an overestimated stock market integration, leading to the empirical fallacy that these markets are becoming more tightly linked and mutually influential, but in fact their interconnectedness remains at a low level in the absence of common shocks from the broader world market. Without the influences from the international stock market, the real cross-market linkages during calm times in the East and Southeast Asian region are shown to be rather weak, suggesting potential diversification benefits for international investors.

Our empirical results show that the interconnection among the ASEAN5+4 stock markets tends to vary over time. It rises sharply when the crisis unfolds, as all markets are commonly prone to risk spillovers from the international market. During the crisis period, cross-market connection peaks, implying diminishing diversification benefits in these markets when they are simultaneously experiencing turbulences caused by systemic events. In the post-crisis period, market interconnectedness declines to a quite low level. A plausible explanation is that these markets, after undergoing the financial crisis, become more alert to information and risk spillovers from external sources, especially neighbour markets, making them more prudent and independent from other markets in the region.

We also find a time-variant network structure, with changing importance of individual markets (nodes) and time-varying links, based on both MST and VAR results. On average, Singapore and Hong Kong exert the strongest influences on others, while they are also more prone to shocks and information spillovers from other markets, irrespective of data used. The key roles of these markets are also found before and after the 1997-98 Asian financial crisis in Huyghebaert and Wang (2010). The biggest capital market Japan appears to be the most segmented among all, implying that market size may not matter much for a market's level of integration. China, despite its large market size and strikingly rapid growth over the past decade, is among the least affected or influential markets. We also find the rising role of Indonesia in the network after filtering the world stock market effects, as opposed to South Korea based on non-filtered data. The divergence in the degree of integration among these markets can be attributed to the different levels of stock market development (Singh, 2009), as well as political, economic and institutional differences across jurisdictions in this region (Yu et al., 2010).

Some practical implications from our findings can aid and nourish potential users in the process of policy making and making asset allocation decisions. For policy makers, our results indicate that there is still a long way to go to achieve a high level of capital market integration within the ASEAN5+4 markets and the broader Asian market. Integration efforts should be jointly made on multiple aspects to foster and bolster regional integration, through for example, bilateral agreements, establishing exchange linkages, facilitating cross-border trading of stocks, etc. From the financial stability perspective, by identifying these key stock markets in the region, we provide strong policy recommendations with respect to carefully watching and regulating these markets with *ex ante* inoculation plans in places, so as to protect not only those core markets but more importantly, a substantial part of the network during crises. For international investors seeking for potential investment opportunities in the Asian market, our results suggest that international portfolio diversification benefits are still highly relevant in these Asian markets. We hope this study can provide a new perspective of understanding and analysing the trends and patterns of stock market integration, not only in East and Southeast Asia but generalizable to other markets and regions.

CONCLUDING REMARKS

This thesis consists of three highly related studies, unanimously seeking to empirically model several facets of systemic risk and its possible spillover mechanisms and trajectories. The concluding remarks aim to summarise the main theories underlying this thesis and core quantitative methodologies adopted, as well as the most significant contributions to the extant literature of modelling systemic risk and implications it provides to financial market participants. Discussions on the limitations and future research directions are also included.

The empirical studies in this thesis are mainly drawn on two paradigms, the portfolio theory and the network theory, which are introduced and discussed in a review of relevant literature in Chapter 1. These theories form two mainstreams that many academic researches dedicated to quantitively studying systemic risk are inclined to follow, and direct the analyses in the following chapters.

In the spirit of the portfolio theory, Chapters 2 and 3 are both based on the idea of capturing individual components' contributions to the risk of the whole market, or from an opposite direction, detecting how the risk dynamics in the market may affect individual components' risk status. The construction of the risk measures adopted in these chapters, including Marginal Expected Shortfall (Acharya et al., 2017), Component Expected Shortfall (Banulescu and Dumitrescu, 2015), Conditional Value at Risk and Delta Conditional Value at Risk (Adrian and Brunnermeier, 2016), takes a portfolio perspective by viewing the entire market as one portfolio composed of its constituent firms or sectors. By looking into the connection and interactions between the portfolio's overall risk and its constituent components' individual risk, we manage to acquire the risk information with respect to which market components are systemically important, and how risk tends to spill over between the whole market and these systemically important financial institutions (SIFIs) or systemically important sectors (SISs).

The main paradigm at the heart of Chapter 4 is the network theory. Drawn on the seminal work of Allen and Gale (2000b), the interconnectedness among market components may give rise to a structural vulnerability that may induce risk propagation and threaten the system-wide financial stability. In the vine of quantitative network methods, Chapter 4 explicitly measures the interdependence among several East and Southeast Asian stock markets, to investigate the level of integration among them. The network topology showcases the most important market that plays a role in enhancing financial market integration in this region. The seemingly high interconnectedness among these markets is found to be largely driven by the global market effects that they are commonly exposed to.

To serve the purpose of identifying systemically important risk contributors, several recently developed seminal quantitative methods based on high frequency (daily or weekly) market data are adopted, such as Marginal Expected Shortfall (MES) (Acharya et al., 2017) , Component Expected Shortfall (CES) (Banulescu and Dumitrescu, 2015), dynamic copula (Patton, 2012), Conditional Value at Risk (Adrian and Brunnermeier, 2016), and a VAR-based approach by Diebold and Yilmaz (2014). Several classic time series model specifications are also applied, such as a dynamic conditional correlation (DCC) model with a GJR-GARCH (1,1) process for estimating MES and CES in Chapter 2, and an ARMA-GARCH specification for estimating marginal distributions of return series in Chapter 3. While attempting to depict the time-varying network structure formed by the financial markets in Chapter 4, we apply the minimum spanning tree, a powerful tool generated from Graph theory, to capturing the interconnectedness between markets, and to spotting the central nodes in this network that may play vital roles in transmitting whatever is flowing through the network, such as information and risk.

No matter which paradigm or methodology applied, time variation is a non-negligible trait of any financial market and systemic risk in it. For developing markets that our samples are mainly composed of in this thesis, this is particularly true. Most of these markets are experiencing on-going reforms, constant policy and regulatory updates, progress in technologies and financial innovations, and financial market liberalization. These changes from endogenous sources plus unpredictable exogenous shocks from the international market lead to time-varying market conditions, making the financial markets increasingly complex and adaptive. A static snapshot may offer a perfect overview of the average status of systemic risk over a given time span and render a general idea of a market's risk level. It is, however, hardly satisfactory to use this type of static information to underpin risk-related investment decision making or policy making in the presence of ever-evolving market conditions. Bearing this in mind, we try to investigate the multiple facets of systemic risk under a dynamic setting by including the time dimension throughout the analysis in this thesis. The time-varying characteristics of the market interconnectedness and systemic risk dynamics documented in this thesis well prove the necessity of taking the time dimension into account.

Notably, the empirical studies in this thesis account for tail risk dependence not only between firms and the financial market as in Chapter 3, but also between sectors and the market as studied in Chapter 2. Gauging systemic risk by considering extreme events is informative and renders useful implications to market participants for decision-making during both calm and crisis periods. By considering the likely patterns of risk spillovers during extreme events, policy makers may pay more attention to the key financial institutions to identify early warning signals that impend threats to financial stability, as well as to pinpoint underperforming policies and unintended consequences. Meanwhile, investigating the effects of tail events help information users locate the most important risk contributors and trace possible risk spillover trajectories once a tail event occurs, which is critical for crisis management and help regulators make *ex ante* inoculation plans and ensure they are in place to protect a substantial part of the market during turmoil periods.

In these chapters, much attention is paid to the rising economy of China. The miracle of China's economy and the direction it is steering towards have been a thriving research field in recent years. With respect to financial markets, while developed western markets have been intensively studied in the literature, much less light has been cast on China's market, although it increasingly engages in and exerts significant influences on the global economy. Notwithstanding the phenomenal economic growth and fast stock market expansion in the past decades, the "New Normal" economy of China is experiencing slowdown in growth and faces perpetuating problems arising from both domestic and global sources. With the deepening of the Sino-US trade war, economic policy uncertainties keep building up (Zhang et al., 2019), inflicting mounting anxiety of feeble growth and hesitation of businesses to invest. The recent frequent stock market crashes in China touch the nerves of many domestic and global investors and market watchers, among whom fears of a financial calamity weight on the sentiment. Against this backdrop, we argue that the systemic risk in the Chinese market is of unprecedented great importance to financial stability not only in the domestic but also the global market.

By examining the integration among the Chinese stock market and its neighbouring Asian markets, Chapter 4 addresses a research question clearly relevant to both international investors and regional policy makers. The former need to understand market integration related to their asset allocation decisions to correctly evaluate cross-market diversification benefits. The latter need to assess the actual achieved level of market integration against their desired level of integration. Whilst a time-varying level of integration is documented, the role of the global factor is identified using a filtering approach constructed on the basis of an international capital asset pricing model (ICAPM). Echoing the existing empirical evidence, the critical role of financial crisis in strengthening the interconnectedness is also confirmed in this study.

Regarding potential expansions to this thesis, there could be several directions to go deeper and broader. Specifically, Chapter 4 clearly argues the importance for both global investors and authorities to understand the drivers of and barriers to integration. However, it has to be mentioned that this is where this research falls short. Beyond identifying the time-varying level of integration and the role of a ‘global factor’ causing overestimated interconnectedness across markets, further insights could be provided concerning the drivers and barriers to regional financial integration. By disentangling the roles of these factors, we may create more insights into understanding the complex mechanism of financial market integration, that authorities and governments could refer to when gearing policy efforts more efficiently and effectively towards a more integrated regional market, so as to promote local stock markets’ financial openness and governance, enhance their risk absorption capability and competitiveness, and bolster regional financial stability.

Within the framework of portfolio models, other elements such as particular shocks to the financial system that trigger systemic events (such as asset price misalignments) can be considered. More dimensions at the corporate level could also be added when investigating institutional-level risk contributions and evaluating individual firms' systemic importance. Accounting datasets, despite concerns on, for example, their low frequency and lags, transparency and data quality issues and non-uniform disclosure standards, can be combined with high frequency market data to improve the forecast power of systemic risk models and aid potential users to more precisely detect and predict risk spillover patterns.

Regarding the network models, new techniques such as those focusing on distinguishing the multiple layers of network and their varied roles in enabling risk transmission can be further employed, to conduct more in-depth and comprehensive investigation on the underlying structure of the interconnectedness network. On the other hand, besides information and risk spillovers, it is also interesting to consider other types of contagion across this network, such as uncertainties (Labidi et al., 2018) and investors' sentiment (Baker and Wurgler, 2006), which may act as an amplification mechanism of risk spillovers and are usually mingled with each other, therefore having been scarcely studied to the best of our knowledge.

When studying financial market integration, some potential contributors could be included in future research, such as some key macroeconomic indicators and legal environments. Within the framework of behavioural finance, investors' behaviour should be an important piece that can help solve the puzzle of financial market integration. The extant literature argues that local stock markets are affected by local as well as global investors, while the latter may suffer more from a global systemic event and accordingly adjust their investment behaviour, such as increasing their home bias during crises (Coval and Moskowitz, 1999; Aggarwal et al., 2012). By contrast, local investors tend to be less prone to global crises (unless in cases of severe risk spillovers form the global market). Our evidence of market interconnectedness in Chapter 4 should be the results of the combined behaviour of both investor types. It is a potentially interesting research topic to disentangle each group's contribution to the regional financial market integration.

Geographically, we focus on Asian financial markets in this thesis, but hope to provide new perspectives for understanding and analysing the trends and patterns of systemic risk spillovers and financial market integration, not only in Asia but also generalizable to other markets and regions.

LIST OF REFERENCES

Abadie, A. 2002. Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American statistical Association,* 97**,** 284-292.

Abid, I., Kaabia, O. & Guesmi, K. 2014. Stock market integration and risk premium: Empirical evidence for emerging economies of South Asia. *Economic Modelling,* 37**,** 408-416.

Acemoglu, D., Ozdaglar, A. & Tahbaz-Salehi, A. 2015. Systemic risk and stability in financial networks. *American Economic Review,* 105**,** 564-608.

Acharya, V., Engle, R. & Richardson, M. 2012. Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review,* 102**,** 59-64.

Acharya, V. & Naqvi, H. 2012. The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics,* 106**,** 349-366.

Acharya, V. V. 2009. A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability,* 5**,** 224-255.

Acharya, V. V., Gale, D. & Yorulmazer, T. 2011. Rollover risk and market freezes. *The Journal of Finance,* 66**,** 1177-1209.

Acharya, V. V., Pedersen, L., Philippon, T. & Richardson, M. 2013. Taxing Systemic Risk. *In:* Roggi, O. & Altman, E. (eds.) *Managing and Measuring Risk: Emerging Global Standards and Regulations After the Financial Crisis.*

Acharya, V. V., Pedersen, L. H., Philippon, T. & Richardson, M. 2017. Measuring Systemic Risk. *The Review of Financial Studies,* 30**,** 2-47.

Acharya, V. V. & Richardson, M. 2009. Causes of the financial crisis. *Critical Review,* 21**,** 195-210.

Acharya, V. V. & Skeie, D. 2011. A model of liquidity hoarding and term premia in inter-bank markets. *Journal of Monetary Economics,* 58**,** 436-447.

Acharya, V. V. & Viswanathan, S. 2011. Leverage, Moral Hazard, and Liquidity. *Journal of Finance,* 66**,** 99-138.

Acharya, V. V. & Yorulmazer, T. 2008a. Cash-in-the-Market Pricing and Optimal Resolution of Bank Failures. *The Review of Financial Studies,* 21**,** 2705-2742.

Acharya, V. V. & Yorulmazer, T. 2008b. Information contagion and bank herding. *Journal of money, credit and Banking,* 40**,** 215-231.

Asian Development Bank (ADB). 2018. Asian Economics Integration Report 2018.

Adrian, T. & Brunnermeier, M. K. 2016. CoVaR. *American Economic Review,* 106**,** 1705-41.

Adrian, T. & Shin, H. S. 2010. Liquidity and leverage. *Journal of Financial Intermediation,* 19**,** 418-437.

Adrian, T. & Shin, H. S. 2014. Procyclical Leverage and Value-at-Risk. *Review of Financial Studies,* 27**,** 373-403.

Afonso, G. & Shin, H. S. 2011. Precautionary demand and liquidity in payment systems. *Journal of Money, Credit and Banking,* 43**,** 589-619.

Aggarwal, R., Kearney, C. & Lucey, B. 2012. Gravity and culture in foreign portfolio investment. *Journal of Banking & Finance,* 36**,** 525-538.

Aityan, S. K., Ivanov-Schitz, A. K. & Izotov, S. S. 2010. Time-shift asymmetric correlation analysis of global stock markets. *Journal of International Financial Markets, Institutions and Money,* 20**,** 590-605.

Aiyar, S., Calomiris, C. W., Hooley, J., Korniyenko, Y. & Wieladek, T. 2014. The

international transmission of bank capital requirements: Evidence from the UK. *Journal of Financial Economics,* 113**,** 368-382.
Al Nasser, O. M. & Hajilee, M. 2016. Integration of emerging stock markets with global stock markets. *Research in International Business and Finance,* 36**,** 1-12.
Aldasoro, I. & Angeloni, I. 2015. Input–output-based measures of systemic importance. *Quantitative Finance,* 15**,** 589-606.
Allen, F. & Babus, A. 2009. Networks in finance. In: Kleindorfer, P., Wind, Y. & Gunther, R. (eds.) *The network challenge: strategy, profit, and risk in an interlinked world*. Pearson Education, Inc.
Allen, F., Babus, A. & Carletti, E. 2009. Financial crises: theory and evidence. *Annual Review of Financial Economics,* 1**,** 97-116.
Allen, F., Babus, A. & Carletti, E. 2012. Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics,* 104**,** 519-534.
Allen, F. & Carletti, E. 2013. Systemic risk from real estate and macro-prudential regulation. *International Journal of Banking, Accounting and Finance,* 5**,** 28-48.
Allen, F. & Gale, D. 2000a. Bubbles and crises. *The economic journal,* 110**,** 236-255.
Allen, F. & Gale, D. 2000b. Financial contagion. *Journal of political economy,* 108**,** 1-33.
Allen, F., Qian, J. Q. & Gu, X. 2017. An Overview of China's Financial System. *Annual Review of Financial Economics,* 9**,** 191-231.
Allen, F., Qian, J. Q., Shan, S. C. & Zhao, M. 2014. The IPO of Industrial and Commercial Bank of China and the 'Chinese Model' of privatizing large financial institutions. *The European Journal of Finance,* 20, 599-624.
Alotaibi, A. R. & Mishra, A. V. 2017. Time varying international financial integration for GCC stock markets. *The Quarterly Review of Economics and Finance,* 63**,** 66-78.
Anginer, D., Demirguc-Kunt, A. & Zhu, M. 2014. How does competition affect bank systemic risk? *Journal of Financial Intermediation,* 23**,** 1-26.
Arouri, M. E. H. & Foulquier, P. 2012. Financial market integration: Theory and empirical results. *Economic Modelling,* 29**,** 382-394.
Artzner, P., Delbaen, F., Eber, J. M. & Heath, D. 1999. Coherent measures of risk. *Mathematical finance,* 9**,** 203-228.
ASEAN, Secretariat. 2015. ASEAN Economic Community Blueprint 2025. Jakarta.
Baker, M. & Wurgler, J. 2006. Investor sentiment and the cross‐section of stock returns. *The journal of finance,* 61**,** 1645-1680.
Bala, D. A. & Takimoto, T. 2017. Stock markets volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. *Borsa Istanbul Review,* 17**,** 25-48.
Ball, R. 2016. IFRS–10 years later. *Accounting and Business Research,* 46**,** 545-571.
Banulescu, G.-D. & Dumitrescu, E.-I. 2015. Which are the SIFIs? A Component Expected Shortfall approach to systemic risk. *Journal of Banking & Finance,* 50**,** 575-588.
Battaglia, F. & Gallo, A. 2013. Securitization and systemic risk: An empirical investigation on Italian banks over the financial crisis. *International Review of Financial Analysis,* 30**,** 274-286.
Basel Committee on Banking Supervision (BCBS). 2011. Consultative Document: Global systemically important banks: Assessment methodology and the additional loss absorbency requirement.
Basel Committee on Banking Supervision (BCBS). 2013. Global systemically important

banks: updated assessment methodology and the higher loss absorbency requirement.
Beine, M., Cosma, A. & Vermeulen, R. 2010. The dark side of global integration: Increasing tail dependence. *Journal of Banking & Finance,* 34**,** 184-192.
Bekaert, G. & Harvey, C. R. 1995. Time‐varying world market integration. *the Journal of Finance,* 50**,** 403-444.
Bekaert, G. & Harvey, C. R. 2003. Emerging markets finance. *Journal of Empirical Finance,* 10**,** 3-55.
Bekiros, S. D. 2014. Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis,* 33**,** 58-69.
Benoit, S., Colliard, J.-E., Hurlin, C. & Pérignon, C. 2017. Where the risks lie: A survey on systemic risk. *Review of Finance,* 21**,** 109-152.
Benoit, S., Hurlin, C. & Pérignon, C. 2015. Implied risk exposures. *Review of Finance,* 19**,** 2183-2222.
Benoit, S., Hurlin, C. & Pérignon, C. 2018. Pitfalls in systemic-risk scoring. *Journal of Financial Intermediation,* 39**,** 19-44.
Berger, A. N., Hancock, D. & Marquardt, J. C. 1996. A framework for analyzing efficiency, risks, costs, and innovations in the payments system. *Journal of Money, Credit and Banking,* 28**,** 696-732.
Bernal, O., Gnabo, J.-Y. & Guilmin, G. 2014. Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking & Finance,* 47**,** 270-287.
Bernanke, B. & Gertler, M. 1989. Agency costs, net worth, and business fluctuation. *American Economic Review,* 79**,** 14-31.
Bernanke, B., Gertler, M. & Gilchrist, S. 1996. The Financial Accelerator and the Flight to Quality. *The Review of Economics and Statistics,* 78**,** 1-15.
Bernanke, B. S. 2009. Federal Reserve programs to strengthen credit markets and the economy: testimony before the Committee on Financial Services, US House of Representatives, February 10, 2009. Board of Governors of the Federal Reserve System (US).
Bernardi, M., Durante, F. & Jaworski, P. 2017. CoVaR of families of copulas. *Statistics & Probability Letters,* 120**,** 8-17.
Betz, F., Hautsch, N., Peltonen, T. A. & Schienle, M. 2016. Systemic risk spillovers in the European banking and sovereign network. *Journal of Financial Stability,* 25**,** 206-224.
Bhattacharya, S. & Gale, D. 1987. Preference shocks, liquidity, and central bank policy. *In:* Singleton, K. J. & Barnett, W. A. (eds.) *New Approaches to Monetary Economics: Proceedings of the Second International Symposium in Economic Theory and Econometrics.* Cambridge: Cambridge University Press.
Bhattacharya, S., Tsomocos, D., Goodhart, C. & Vardoulakis, A. 2011. Minsky's financial instability hypothesis and the leverage cycle. *London School of Economics FMG Special Paper*.
Bhattacharya, U. & Daouk, H. 2002. The world price of insider trading. *The Journal of Finance,* 57**,** 75-108.
Biais, B., Mariotti, T., Rochet, J. C. & Villeneuve, S. 2010. Large risks, limited liability, and dynamic moral hazard. *Econometrica,* 78**,** 73-118.
Bianchi, J. & Mendoza, E. G. 2018. Optimal time-consistent macroprudential policy. *Journal*

of Political Economy, 126**,** 588-634.
Billio, M., Donadelli, M., Paradiso, A. & Riedel, M. 2017. Which market integration measure? *Journal of Banking & Finance,* 76**,** 150-174.
Billio, M., Getmansky, M., Lo, A. W. & Pelizzon, L. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics,* 104**,** 535-559.
Bisias, D., Flood, M., Lo, A. W. & Valavanis, S. 2012. A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics, Vol 4,* 4**,** 255-296.
Blei, S. & Ergashev, B. 2014. Asset commonality and systemic risk among large banks in the United States. Available at SSRN: https://ssrn.com/abstract=2503046.
Boissay, F., Collard, F. & Smets, F. 2016. Booms and banking crises. *Journal of Political Economy,* 124**,** 489-538.
Bollerslev, T. & Wooldridge, J. M. 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric reviews,* 11**,** 143-172.
Bolton, P., Santos, T. & Scheinkman, J. A. 2011. Outside and inside liquidity. *The Quarterly Journal of Economics,* 126**,** 259-321.
Bonga-Bonga, L. 2018. Uncovering equity market contagion among BRICS countries: An application of the multivariate GARCH model. *The Quarterly Review of Economics and Finance,* 67**,** 36-44.
Bongini, P., Nieri, L. & Pelagatti, M. 2015. The importance of being systemically important financial institutions. *Journal of Banking & Finance,* 50**,** 562-574.
Borio, C. 2003. Towards a macroprudential framework for financial supervision and regulation? *CESifo Economic Studies,* 49**,** 181-215.
Borio, C. E. & Drehmann, M. 2009. Assessing the risk of banking crises–revisited.
Boss, M., Elsinger, H., Summer, M. & Thurner 4, S. 2004. Network topology of the interbank market. *Quantitative finance,* 4**,** 677-684.
Boubaker, S., Jouini, J. & Lahiani, A. 2016. Financial contagion between the US and selected developed and emerging countries: The case of the subprime crisis. *The Quarterly Review of Economics and Finance,* 61**,** 14-28.
Boubakri, S. & Guillaumin, C. 2015. Regional integration of the East Asian stock markets: An empirical assessment. *Journal of International Money and Finance,* 57**,** 136-160.
Bouvard, M., Chaigneau, P. & Motta, A. D. 2015. Transparency in the financial system: Rollover risk and crises. *The Journal of Finance,* 70**,** 1805-1837.
Brownlees, C. & Engle, R. F. 2017. SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *The Review of Financial Studies,* 30**,** 48-79.
Brownlees, C. T. & Engle, R. 2012. Volatility, correlation and tails for systemic risk measurement. *Available at SSRN,* doi: 10.2139/ssrn.1611229.
Brunnermeier, M., Gorton, G. & Krishnamurthy, A. 2014. Liquidity mismatch measurement. *In:* Brunnermeier, M. & Krishnamurthy, A. (eds.) *Risk topography: Systemic risk and macro modeling.* University of Chicago Press.
Brunnermeier, M. K., Eisenbach, T. M. & Sannikov, Y. 2013. Macroeconomics with financial frictions: A survey. *In:* Acemoglu, D., Arellano, M. & Dekel, E. (eds.) *Advances in Economics and Econometrics, Tenth World Congress of the Econometric Society, Vol. II: Applied Economics,* New York: Cambridge University Press, New York. pp. 4-94.
Brunnermeier, M. K. & Oehmke, M. 2013a. Bubbles, financial crises, and systemic risk.

Handbook of the Economics of Finance. Elsevier.
Brunnermeier, M. K. & Oehmke, M. 2013b. The maturity rat race. *The Journal of Finance,* 68**,** 483-521.
Brunnermeier, M. K. & Pedersen, L. H. 2009. Market Liquidity and Funding Liquidity. *The Review of Financial Studies,* 22**,** 2201-2238.
Brunnermeier, M. K. & Sannikov, Y. 2014. A macroeconomic model with a financial sector. *American Economic Review,* 104**,** 379-421.
Buccheri, G., Marmi, S. & Mantegna, R. N. 2013. Evolution of correlation structure of industrial indices of US equity markets. *Physical Review E,* 88(1)**,** 012806. https://doi.org/10.1103/PhysRevE.88.012806.
Burdekin, R. C. K. & Siklos, P. L. 2012. Enter the dragon: Interactions between Chinese, US and Asia-Pacific equity markets, 1995–2010. *Pacific-Basin Finance Journal,* 20**,** 521-541.
Cabrales, A., Gottardi, P. & Vega-Redondo, F. 2017. Risk sharing and contagion in networks. *The Review of Financial Studies,* 30**,** 3086-3127.
Caccioli, F., Marsili, M. & Vivo, P. 2009. Eroding market stability by proliferation of financial instruments. *The European Physical Journal B,* 71**,** 467. https://doi.org/10.1140/epjb/e2009-00316-y.
Candelon, B. & Tokpavi, S. 2016. A Nonparametric Test for Granger Causality in Distribution With Application to Financial Contagion. *Journal of Business & Economic Statistics,* 34**,** 240-253.
Caporale, G. M. & You, K. 2017. Stock Market Integration in Asia: Global or Regional? Evidence from Industry Level Panel Convergence Tests. *DIW Berlin Discussion Paper No. 1669,* http://dx.doi.org/10.2139/ssrn.2972020.
Carrieri, F., Errunza, V. & Hogan, K. 2007. Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis,* 42**,** 915-940.
Castiglionesi, F., Feriozzi, F. & Lorenzoni, G. 2017. Financial integration and liquidity crises. *Management Science*. 65(3), 955-975.
Castro, C. & Ferrari, S. 2014. Measuring and testing for the systemically important financial institutions. *Journal of Empirical Finance,* 25**,** 1-14.
Cecchetti, S. G. 2015. The road to financial stability: Capital regulation, liquidity regulation, and resolution. *International Journal of Central Banking,* 11**,** 127-139.
Chao, S.-K., Härdle, W. K. & Wang, W. 2015. Quantile regression in risk calibration. *In:* Lee, C.-F. & Lee, J. C. (eds.) *Handbook of financial econometrics and statistics.* New York: Springer.
Chari, A. & Henry, P. B. 2004. Risk sharing and asset prices: evidence from a natural experiment. *The Journal of Finance,* 59**,** 1295-1324.
Chen, M.-P., Chen, P.-F. & Lee, C.-C. 2014a. Frontier stock market integration and the global financial crisis. *The North American Journal of Economics and Finance,* 29**,** 84-103.
Chen, P. 2018. Understanding international stock market comovements: A comparison of developed and emerging markets. *International Review of Economics & Finance,* 56**,** 451-464.
Chen, Y. 1999. Banking panics: The role of the first-come, first-served rule and information externalities. *Journal of Political Economy,* 107**,** 946-968.
Chen, Y., Shi, Y., Wei, X. & Zhang, L. 2014b. Domestic systemically important banks: a quantitative analysis for the Chinese banking system. *Mathematical Problems in*

Engineering, Vol. 2014. https://doi.org/10.1155/2014/819371.
Cherubini, U., Luciano, E. & Vecchiato, W. 2004. *Copula methods in finance,* John Wiley & Sons.
Chien, M.-S., Lee, C.-C., Hu, T.-C. & Hu, H.-T. 2015. Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Economic Modelling,* 51**,** 84-98.
Chinazzi, M. & Fagiolo, G. 2015. Systemic risk, contagion, and financial networks: A survey. *Institute of Economics, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM) Working Paper Series*.
Chowdhury, B., Dungey, M., Kangogo, M., Sayeed, M. A. & Volkov, V. 2019. The changing network of financial market linkages: The Asian experience. *International Review of Financial Analysis,* 64**,** 71-92.
Cifuentes, R., Ferrucci, G. & Shin, H. S. 2005. Liquidity Risk and Contagion. *Journal of the European Economic Association,* 3**,** 556-566.
Corsi, F., Lillo, F., Pirino, D. & Trapin, L. 2018. Measuring the propagation of financial distress with Granger-causality tail risk networks. *Journal of Financial Stability,* 38**,** 18-36.
Coval, J. D. & Moskowitz, T. J. 1999. Home Bias at Home: Local Equity Preference in Domestic Portfolios. *The Journal of Finance,* 54**,** 2045-2073.
Creti, A. & Nguyen, D. K. 2015. Energy markets′ financialization, risk spillovers, and pricing models. *Energy Policy,* 82**,** 260-263.
Cubillas, E. & González, F. 2014. Financial liberalization and bank risk-taking: International evidence. *Journal of Financial Stability,* 11**,** 32-48.
Danielsson, J., James, K. R., Valenzuela, M. & Zer, I. 2016. Model risk of risk models. *Journal of Financial Stability,* 23**,** 79-91.
DaníElsson, J., Shin, H. S. & Zigrand, J.-P. 2004. The impact of risk regulation on price dynamics. *Journal of Banking & Finance,* 28**,** 1069-1087.
De Bandt, O. & Hartmann, P. 2002. *Systemic Risk: A Survey,* Oxford, Oxford University Press.
De La Torre, A., Gozzi, J. C. & Schmukler, S. L. 2007. Stock market development under globalization: Whither the gains from reforms? *Journal of Banking & Finance,* 31**,** 1731-1754.
De Nicolò, G. & Juvenal, L. 2014. Financial integration, globalization, and real activity. *Journal of Financial Stability,* 10**,** 65-75.
De Nicolò, G. & Kwast, M. L. 2002. Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance,* 26**,** 861-880.
De Nicolò, G. & Lucchetta, M. 2013. Systemic risks and the macroeconomy. *In:* Haubrich, J. G. & Lo, A. W. (eds.) *Quantifying Systemic Risk*. National Bureau of Economic Research.
Deeley, K. 2016. Exploring Risk Contagion Using Graph Theory and Markov Chains. *Mathworks*.
Degryse, H. & Nguyen, G. 2007. Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking,* 3**,** 123-171.
Diamond, D. W. 1984. Financial intermediation and delegated monitoring. *The review of economic studies,* 51**,** 393-414.

Diamond, D. W. & Dybvig, P. H. 1983. Bank runs, deposit insurance, and liquidity. *Journal of political economy,* 91**,** 401-419.
Diamond, D. W. & Rajan, R. G. 2005. Liquidity shortages and banking crises. *The Journal of finance,* 60**,** 615-647.
Diamond, D. W. & Rajan, R. G. 2011. Fear of fire sales, illiquidity seeking, and credit freezes. *The Quarterly Journal of Economics,* 126**,** 557-591.
Diebold, F. X. & Yilmaz, K. 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *Economic Journal,* 119**,** 158-171.
Diebold, F. X. & Yilmaz, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting,* 28**,** 57-66.
Diebold, F. X. & Yilmaz, K. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics,* 182**,** 119-134.
Dijkstra, E. W. 1959. A note on two problems in connexion with graphs. *Numerische mathematik,* 1**,** 269-271.
Dimitriou, D., Kenourgios, D. & Simos, T. 2013. Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis,* 30**,** 46-56.
Djauhari, M. A. & Gan, S. L. 2016. Network topology of economic sectors. *Journal of Statistical Mechanics: Theory and Experiment,* 2016(9)**,** 093401. doi:10.1088/1742-5468/2016/09/093401.
Drehmann, M. & Tarashev, N. 2013. Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation,* 22**,** 586-607.
Dudley, W., Hatzius, J. & Mckelvey, E. 2005. Financial conditions need to tighten further. *US Economic Analyst*.
European Central Bank (ECB). 2010. Financial networks and financial stability. *Financial Stability Review***,** 155–160.
Eckernkemper, T. 2018. Modeling Systemic Risk: Time-Varying Tail Dependence When Forecasting Marginal Expected Shortfall. *Journal of Financial Econometrics,* 16**,** 63-117.
Eichengreen, B., Mody, A., Nedeljkovic, M. & Sarno, L. 2012. How the Subprime Crisis went global: Evidence from bank credit default swap spreads. *Journal of International Money and Finance,* 31**,** 1299-1318.
Eisenberg, L. & Noe, T. H. 2001. Systemic Risk in Financial Systems. *Management Science,* 47**,** 236-249.
Elliott, M., Golub, B. & Jackson, M. O. 2014. Financial networks and contagion. *American Economic Review,* 104**,** 3115-53.
Elsinger, H., Lehar, A. & Summer, M. 2006a. Risk assessment for banking systems. *Management science,* 52**,** 1301-1314.
Elsinger, H., Lehar, A. & Summer, M. 2006b. Using market information for banking system risk assessment. *International Journal of Central Banking,* 2**,** 137-165.
Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics,* 20**,** 339-350.
Engle, R. F. 2016. Dynamic conditional beta. *Journal of Financial Econometrics,* 14**,** 643-

667.
Engle, R. F. & Gonzalez-Rivera, G. 1991. Semiparametric ARCH models. *Journal of Business & Economic Statistics,* 9**,** 345-359.
Engle, R. F. & Manganelli, S. 2004. CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics,* 22**,** 367-381.
Esqueda, O. A., Assefa, T. A. & Mollick, A. V. 2012. Financial globalization and stock market risk. *Journal of International Financial Markets, Institutions and Money,* 22**,** 87-102.
Ewing, B. T. 2002. The transmission of shocks among S&P indexes. *Applied Financial Economics,* 12**,** 285-290.
Ewing, B. T., Forbes, S. M. & Payne, J. E. 2003. The effects of macroeconomic shocks on sector-specific returns. *Applied Economics,* 35**,** 201-207.
Fan, X.-Q., Du, M.-D. & Long, W. 2017. Risk Spillover Effect of Chinese Commercial Banks: Based on Indicator Method and CoVaR Approach. *Procedia Computer Science,* 122**,** 932-940.
Fang, L., Sun, B., Li, H. & Yu, H. 2018a. Systemic risk network of Chinese financial institutions. *Emerging Markets Review,* 35**,** 190-206.
Fang, L., Xiao, B., Yu, H. & You, Q. 2018b. A stable systemic risk ranking in China's banking sector: Based on principal component analysis. *Physica A: Statistical Mechanics and its Applications,* 492**,** 1997-2009.
Farhi, E. & Tirole, J. 2012. Collective moral hazard, maturity mismatch, and systemic bailouts. *American Economic Review,* 102**,** 60-93.
Feng, S., Huang, S., Qi, Y., Liu, X., Sun, Q. & Wen, S. 2018. Network features of sector indexes spillover effects in China: A multi-scale view. *Physica A: Statistical Mechanics and its Applications,* 496**,** 461-473.
Flannery, M. J. 1996. Financial crises, payment system problems, and discount window lending. *Journal of money, credit and banking,* 28**,** 804-824.
Forbes, K. & Rigobon, R. 2001. Measuring contagion: conceptual and empirical issues. *In:* Claessens, S. & Forbes, K. J. (eds.) *International financial contagion.* Boston, MA: Springer, US.
Forbes, K. J. The "Big C": identifying and mitigating contagion. *MIT Sloan Research Paper No. 4970-12*. Available at SSRN: https://ssrn.com/abstract=2149908.
Freixas, X. & Parigi, B. 1998. Contagion and Efficiency in Gross and Net Interbank Payment Systems. *Journal of Financial Intermediation,* 7**,** 3-31.
Freixas, X., Parigi, B. M. & Rochet, J.-C. 2000. Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of money, credit and banking***,** 611-638.
Freixas, X. & Rochet, J. C. 2013. Taming systemically important financial institutions. *Journal of Money, Credit and Banking,* 45**,** 37-58.
Financial Stability Board (FSB). 2009. Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations. *Report to G20 finance ministers and governors*.
Financial Stability Board (FSB). 2010. Reducing the moral hazard posed by systemically important financial institutions, FSB Recommendations and Time Lines.
Financial Stability Board (FSB). 2011. Policy Measures to Address Systemically Important Financial Institutions

Financial Stability Board (FSB). 2013. 2013 update of group of global systemically important banks (G-SIBs).
Financial Stability Board (FSB). 2016. 2016 list of global systemically important insurers (G-SIIs).
Financial Stability Board (FSB). 2018. 2018 list of global systemically important banks (G-SIBs)
Financial Stability Board (FSB), International Monetary Fund (IMF) & Bank for International Settlements (BIS). 2009. Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations. *Report to the G-20 Finance Ministers and Central Bank Governors*.
Financial Stability Oversight Council (FSOC). 2011. Financial Stability Oversight Council 2011 Annual Report.
Gai, P., Haldane, A. & Kapadia, S. 2011. Complexity, concentration and contagion. *Journal of Monetary Economics,* 58**,** 453-470.
Gale, D. & Yorulmazer, T. 2013. Liquidity hoarding. *Theoretical Economics,* 8**,** 291-324.
Gamba-Santamaria, S., Gomez-Gonzalez, J. E., Hurtado-Guarin, J. L. & Melo-Velandia, L. F. 2017. Stock market volatility spillovers: Evidence for Latin America. *Finance Research Letters,* 20**,** 207-216.
Gang, J. & Qian, Z. 2015. China’s monetary policy and systemic risk. *Emerging Markets Finance and Trade,* 51**,** 701-713.
Gennaioli, N., Shleifer, A. & Vishny, R. W. 2013. A model of shadow banking. *The Journal of Finance,* 68**,** 1331-1363.
Ghosh, A. 2016. How does banking sector globalization affect banking crisis? *Journal of Financial Stability,* 25**,** 70-82.
Ghulam, Y. & Doering, J. 2018. Spillover effects among financial institutions within Germany and the United Kingdom. *Research in International Business and Finance,* 44**,** 49-63.
Giesecke, K. & Kim, B. 2011. Systemic risk: What defaults are telling us. *Management Science,* 57**,** 1387-1405.
Giglio, S., Kelly, B. & Pruitt, S. 2016. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics,* 119**,** 457-471.
Gilmore, C. G. & Mcmanus, G. M. 2002. International portfolio diversification: US and Central European equity markets. *Emerging Markets Review,* 3**,** 69-83.
Girardi, G. & Ergün, A. T. 2013. Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance,* 37**,** 3169-3180.
Glasserman, P. & Young, H. P. 2015. How likely is contagion in financial networks? *Journal of Banking & Finance,* 50**,** 383-399.
Glick, R. & Hutchison, M. 2013. China's financial linkages with Asia and the global financial crisis. *Journal of International Money and Finance,* 39**,** 186-206.
Glosten, L. R., Jagannathan, R. & Runkle, D. E. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance,* 48**,** 1779-1801.
Gofman, M. 2017. Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. *Journal of Financial Economics,* 124**,** 113-146.
Goodhart, C. A., Kashyap, A. K., Tsomocos, D. P. & Vardoulakis, A. P. 2013. An integrated framework for analyzing multiple financial regulations. *International Journal of*

Central Banking, 9**,** 109-143.
Gower, J. C. 1966. Some Distance Properties of Latent Root and Vector Methods Used in Multivariate Analysis. *Biometrika,* 53**,** 325-338.
Granger, C. W. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society,* 37(3)**,** 424-438.
Granger, C. W. J. 1980. Testing for causality: A personal viewpoint. *Journal of Economic Dynamics and Control,* 2**,** 329-352.
Granger, C. W. J., Robins, R. & Engle, R. F. 1986. Wholesale and retail prices: Bivariate time-series modeling with forecastable error variances. *Model reliability***,** 1-17. MIT Press.
Greenwood, R., Landier, A. & Thesmar, D. 2015. Vulnerable banks. *Journal of Financial Economics,* 115**,** 471-485.
Guichard, S. & Turner, D. 2008. Quantifying the effect of financial conditions on US activity. *OECD Economics Department Working Papers No. 635*. https://doi.org/10.1787/236860073636.
Guidi, F., Savva, C. S. & Ugur, M. 2016. Dynamic co-movements and diversification benefits: The case of the Greater China region, the UK and the US equity markets. *Journal of Multinational Financial Management,* 35**,** 59-78.
Guidi, F. & Ugur, M. 2014. An analysis of South-Eastern European stock markets: Evidence on cointegration and portfolio diversification benefits. *Journal of International Financial Markets, Institutions and Money,* 30**,** 119-136.
Gupta, R. & Guidi, F. 2012. Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets. *International Review of Financial Analysis,* 21**,** 10-22.
Hakkio, C. S. & Keeton, W. R. 2009. Financial stress: what is it, how can it be measured, and why does it matter? *Economic Review (Kansas City),* 94**,** 5-52.
Hakwa, B., Jäger-Ambrożewicz, M. & Rüdiger, B. 2015. Analysing systemic risk contribution using a closed formula for conditional value at risk through copula. *Communications on Stochastic Analysis,* 9**,** 8.
Haldane, A. G. & Hall, S. G. 1991. Sterling's Relationship with the Dollar and the Deutschemark: 1976-89. *The Economic Journal,* 101**,** 436-443.
Hammoudeh, S. M., Yuan, Y. & Mcaleer, M. 2009. Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets. *The Quarterly Review of Economics and Finance,* 49**,** 829-842.
Hansen, B. E. 1994. Autoregressive conditional density estimation. *International Economic Review,* 35(3)**,** 705-730.
Hao, J. & He, F. 2018. Univariate dependence among sectors in Chinese stock market and systemic risk implication. *Physica A: Statistical Mechanics and its Applications,* 510**,** 355-364.
Härdle, W. K., Wang, W. & Yu, L. 2016. TENET: Tail-Event driven NETwork risk. *Journal of Econometrics,* 192**,** 499-513.
Harvey, C. R. 1993. Portfolio enhancement using emerging markets and conditioning information. *World Bank Discussion Papers 1993***,** 110-110.
Hautsch, N., Schaumburg, J. & Schienle, M. 2014. Financial network systemic risk contributions. *Review of Finance,* 19**,** 685-738.
He, H., Chen, S., Yao, S. & Ou, J. 2015. Stock market interdependence between China and

the world: A multi-factor R-squared approach. *Finance Research Letters,* 13**,** 125-129.
He, Z. & Krishnamurthy, A. 2014. A macroeconomic framework for quantifying systemic risk. National Bureau of Economic Research.
He, Z. & Xiong, W. 2012. Rollover risk and credit risk. *The Journal of Finance,* 67**,** 391-430.
Hemche, O., Jawadi, F., Maliki, S. B. & Cheffou, A. I. 2016. On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation–multivariate GARCH approach. *Economic Modelling,* 52**,** 292-299.
Hirshleifer, D., Subrahmanyam, A. & Titman, S. 1994. Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance,* 49**,** 1665-1698.
Hmissi, B., Bejaoui, A. & Snoussi, W. 2017. On identifying the domestic systemically important banks: The case of Tunisia. *Research in International Business and Finance,* 42**,** 1343-1354.
Holmstrom, B. & Tirole, J. 1997. Financial intermediation, loanable funds, and the real sector. *the Quarterly Journal of economics,* 112**,** 663-691.
Hong, Y., Liu, Y. & Wang, S. 2009. Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics,* 150**,** 271-287.
Huang, Q., De Haan, J. & Scholtens, B. 2017. Analysing Systemic Risk in the Chinese Banking System. *Pacific Economic Review,* 24**,** 348-372.
Huang, W.-Q. & Wang, D. 2018a. A return spillover network perspective analysis of Chinese financial institutions' systemic importance. *Physica A: Statistical Mechanics and its Applications,* 509**,** 405-421.
Huang, W.-Q. & Wang, D. 2018b. Systemic importance analysis of chinese financial institutions based on volatility spillover network. *Chaos, Solitons & Fractals,* 114**,** 19-30.
Huang, W.-Q., Zhuang, X.-T., Yao, S. & Uryasev, S. 2016. A financial network perspective of financial institutions' systemic risk contributions. *Physica A: Statistical Mechanics and its Applications,* 456**,** 183-196.
Huang, X., Zhou, H. & Zhu, H. 2009. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance,* 33**,** 2036-2049.
Huang, X., Zhou, H. & Zhu, H. 2012. Systemic risk contributions. *Journal of financial services research,* 42**,** 55-83.
Hussain, S. I. & Li, S. 2018. The dependence structure between Chinese and other major stock markets using extreme values and copulas. *International Review of Economics & Finance,* 56**,** 421-437.
Huyghebaert, N. & Wang, L. 2010. The co-movement of stock markets in East Asia: Did the 1997–1998 Asian financial crisis really strengthen stock market integration? *China Economic Review,* 21**,** 98-112.
International Association of Insurance Supervisors (IAIS). 2013. Global Systemically Important Insurers: Initial Assessment Methodology.
International Association of Insurance Supervisors (IAIS). 2016. Global Systemically Important Insurers: Updated Assessment Methodology.
International Monetary Fund (IMF). 2006. Financial Soundness Indicators: Compilation Guide.
International Monetary Fund (IMF). 2009. Global Financial Stability Report: Responding to the Financial Crisis and Measuring Systemic Risks. *World Economic and Financial*

Surveys.
Jan, Y.-C., Chou, P. S.-R. & Hung, M.-W. 2000. Pacific Basin stock markets and international capital asset pricing. *Global Finance Journal,* 11**,** 1-16.
Jayasuriya, S. A. 2011. Stock market correlations between China and its emerging market neighbors. *Emerging Markets Review,* 12**,** 418-431.
Jensen, M. C. & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics,* 3**,** 305-360.
Ji, Q., Bouri, E., Roubaud, D. & Shahzad, S. J. H. 2018a. Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Economics,* 75**,** 14-27.
Ji, Q. & Fan, Y. 2016. Evolution of the world crude oil market integration: A graph theory analysis. *Energy Economics,* 53**,** 90-100.
Ji, Q., Liu, B.-Y., Zhao, W.-L. & Fan, Y. 2018b. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. *International Review of Financial Analysis,* doi.org/10.1016/j.irfa.2018.08.002.
Ji, Q., Zhang, D. & Geng, J.-B. 2018c. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production,* 198**,** 972-978.
Jiang, Y., Yu, M. & Hashmi, S. 2017. The Financial Crisis and Co-Movement of Global Stock Markets—A Case of Six Major Economies. *Sustainability,* 9(2)**,** 260. https://doi.org/10.3390/su9020260.
Jin, X. 2018. Downside and upside risk spillovers from China to Asian stock markets: A CoVaR-copula approach. *Finance Research Letters,* 25**,** 202-212.
Joe, H. 1997. Multivariate models and multivariate dependence concepts, Chapman and Hall/CRC.
Johnson, R. & Soenen, L. 2002. Asian economic integration and stock market comovement. *Journal of Financial Research,* 25**,** 141-157.
Kanno, M. 2015. Assessing systemic risk using interbank exposures in the global banking system. *Journal of Financial Stability,* 20**,** 105-130.
Kapadia, S., Drehmann, M., Elliott, J. & Sterne, G. 2012. Liquidity risk, cash flow constraints, and systemic feedbacks. *Quantifying Systemic Risk.* University of Chicago Press.
Karanasos, M., Yfanti, S. & Karoglou, M. 2016. Multivariate FIAPARCH modelling of financial markets with dynamic correlations in times of crisis. *International Review of Financial Analysis,* 45**,** 332-349.
Karimalis, E. N. & Nomikos, N. K. 2018. Measuring systemic risk in the European banking sector: A Copula CoVaR approach. *The European Journal of Finance,* 24**,** 944-975.
Kenourgios, D., Samitas, A. & Paltalidis, N. 2011. Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money,* 21**,** 92-106.
Kim, B.-H., Kim, H. & Lee, B.-S. 2015. Spillover effects of the U.S. financial crisis on financial markets in emerging Asian countries. *International Review of Economics & Finance,* 39**,** 192-210.
Kiyotaki, N. & Moore, J. 1997. Credit cycles. *Journal of political economy,* 105**,** 211-248.
Koop, G., Pesaran, M. H. & Potter, S. M. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics,* 74**,** 119-147.

Korinek, A. 2011. Systemic risk-taking: amplification effects, externalities, and regulatory responses. *Networks Financial Institute Working Paper*, 2011-WP-13.
Kritzman, M., Li, Y., Page, S. & Rigobon, R. 2011. Principal Components as a Measure of Systemic Risk. *The Journal of Portfolio Management*, 37(4)**,** 112-126.
Labidi, C., Rahman, M. L., Hedström, A., Uddin, G. S. & Bekiros, S. 2018. Quantile dependence between developed and emerging stock markets aftermath of the global financial crisis. *International Review of Financial Analysis,* 59**,** 179-211.
Lehar, A. 2005. Measuring systemic risk: A risk management approach. *Journal of Banking & Finance,* 29**,** 2577-2603.
Lehkonen, H. 2014. Stock market integration and the global financial crisis. *Review of Finance*, 19**,** 2039-2094.
Liu, B.-Y., Ji, Q. & Fan, Y. 2017. Dynamic return-volatility dependence and risk measure of CoVaR in the oil market: A time-varying mixed copula model. *Energy Economics,* 68**,** 53-65.
López-Espinosa, G., Moreno, A., Rubia, A. & Valderrama, L. 2012. Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking & Finance,* 36**,** 3150-3162.
Mai, Y., Chen, H. & Meng, L. 2014. An analysis of the sectorial influence of CSI300 stocks within the directed network. *Physica A: Statistical Mechanics and its Applications,* 396**,** 235-241.
Mainik, G. & Schaanning, E. 2014. On dependence consistency of CoVaR and some other systemic risk measures. *Statistics & Risk Modeling,* 31**,** 49-77.
Mantegna, R. & Stanley, H. 2000. An Introduction to Econophysics. *Cambridge, MA*.
Mantegna, R. N. 1999. Hierarchical structure in financial markets. *The European Physical Journal B - Condensed Matter and Complex Systems,* 11**,** 193-197.
Markose, S., Giansante, S. & Shaghaghi, A. R. 2012. 'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior & Organization,* 83**,** 627-646.
Mensi, W., Hammoudeh, S., Nguyen, D. K. & Kang, S. H. 2016. Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics & Finance,* 42**,** 257-276.
Mensi, W., Hammoudeh, S., Shahzad, S. J. H. & Shahbaz, M. 2017. Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance,* 75**,** 258-279.
Meric, I., Ratner, M. & Meric, G. 2008. Co-movements of sector index returns in the world's major stock markets in bull and bear markets: Portfolio diversification implications. *International Review of Financial Analysis,* 17**,** 156-177.
Merrill, C., Nadauld, T., Stulz, R. & Sherlund, S. 2013. Why were there fire sales of mortgage-backed securities by financial institutions during the financial crisis? *Charles A. Dice Center Working Paper No. 2013-02*.
Merton, R. C. 1973. Theory of rational option pricing. *Theory of Valuation***,** 229-288.
Mobarek, A., Muradoglu, G., Mollah, S. & Hou, A. J. 2016. Determinants of time varying co-movements among international stock markets during crisis and non-crisis periods. *Journal of Financial Stability,* 24**,** 1-11.
Moenninghoff, S. C., Ongena, S. & Wieandt, A. 2015. The perennial challenge to counter Too-Big-to-Fail in banking: Empirical evidence from the new international regulation

dealing with Global Systemically Important Banks. *Journal of Banking & Finance,* 61**,** 221-236.
Mollah, S., Quoreshi, A. M. M. S. & Zafirov, G. 2016. Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money,* 41**,** 151-167.
Morris, S. & Shin, H. S. 1999. Risk management with interdependent choice. *Oxford Review of Economic Policy,* 15**,** 52-62.
Narayan, P. K., Mishra, S. & Narayan, S. 2011. Do market capitalization and stocks traded converge? New global evidence. *Journal of Banking & Finance,* 35**,** 2771-2781.
Narayan, S., Sriananthakumar, S. & Islam, S. Z. 2014. Stock market integration of emerging Asian economies: Patterns and causes. *Economic Modelling,* 39**,** 19-31.
Nelsen, R. B. 2006. *An Introduction to Copulas,* Springer.
Nelson, D. B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society***,** 347-370.
Nier, E., Yang, J., Yorulmazer, T. & Alentorn, A. 2007. Network models and financial stability. *Journal of Economic Dynamics and Control,* 31**,** 2033-2060.
Onnela, J.-P., Kaski, K. & Kertész, J. 2004. Clustering and information in correlation based financial networks. *The European Physical Journal B,* 38**,** 353-362.
Orosel, G. O. 1998. Participation costs, trend chasing, and volatility of stock prices. *The Review of Financial Studies,* 11**,** 521-557.
Paligorova, T. & Santos, J. A. 2014. Rollover risk and the maturity transformation function of banks. *Bank of Canada Working Paper*.
Papanikolaou, N. I. & Wolff, C. C. P. 2014. The role of on- and off-balance-sheet leverage of banks in the late 2000s crisis. *Journal of Financial Stability,* 14**,** 3-22.
Patro, D. K., Qi, M. & Sun, X. 2013. A simple indicator of systemic risk. *Journal of Financial Stability,* 9**,** 105-116.
Patton, A. J. 2006. Modelling asymmetric exchange rate dependence. *International economic review,* 47**,** 527-556.
Patton, A. J. 2012. A review of copula models for economic time series. *Journal of Multivariate Analysis,* 110**,** 4-18.
Percival, D. B. & Walden, A. T. 2006. *Wavelet methods for time series analysis,* Cambridge university press.
Perotti, E. C., Ratnovski, L. & Vlahu, R. 2011. Capital regulation and tail risk. *De Nederlandsche Bank Working Paper No. 307*. http://dx.doi.org/10.2139/ssrn.1951899.
Pesaran, H. H. & Shin, Y. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters,* 58**,** 17-29.
Philippe, J. 2001. Value at risk: the new benchmark for managing financial risk. *NY: McGraw-Hill Professional*.
Plekhanov, D. 2017. Quality of China's Official Statistics: A Brief Review of Academic Perspectives. *The Copenhagen Journal of Asian Studies,* 35**,** 76-101.
Prim, R. C. 1957. Shortest connection networks and some generalizations. *The Bell System Technical Journal,* 36**,** 1389-1401.
Pukthuanthong, K. & Roll, R. 2009. Global market integration: An alternative measure and its application. *Journal of Financial Economics,* 94**,** 214-232.
Qiao, H., Xia, Y. & Li, Y. 2016. Can network linkage effects determine return? Evidence from Chinese stock market. *PloS one,* 11(6)**,** e0156784.

https://doi.org/10.1371/journal.pone.0156784.
Ranjeeni, K. 2014. Sectoral and industrial performance during a stock market crisis. *Economic Systems,* 38**,** 178-193.
Reboredo, J. C., Rivera-Castro, M. A. & Ugolini, A. 2016. Downside and upside risk spillovers between exchange rates and stock prices. *Journal of Banking & Finance,* 62**,** 76-96.
Reboredo, J. C. & Ugolini, A. 2015. Systemic risk in European sovereign debt markets: A CoVaR-copula approach. *Journal of International Money and Finance,* 51**,** 214-244.
Rochet, J.-C. & Tirole, J. 1996. Controlling risk in payment systems. *Journal of Money, Credit and Banking,* 28**,** 832-862.
Rodríguez-Moreno, M. & Peña, J. I. 2013. Systemic risk measures: The simpler the better? *Journal of Banking & Finance,* 37**,** 1817-1831.
Rodriguez, J. C. 2007. Measuring financial contagion: A Copula approach. *Journal of Empirical Finance,* 14**,** 401-423.
Rosenberg, M. 2009. Global financial market trends & policy. *Bloomberg Financial Conditions Watch, Vol. 3.*
Sandoval Junior, L., Mullokandov, A. & Kenett, D. Y. 2015. Dependency relations among international stock market indices. *Journal of Risk and Financial Management,* 8**,** 227-265.
Scaillet, O. 2005. Nonparametric estimation of conditional expected shortfall. *Insurance and Risk Management Journal,* 74**,** 639-660.
Schwaab, B., Koopman, S. J. & Lucas, A. 2011. Systemic risk diagnostics: coincident indicators and early warning signals. *ECB Working Paper, No. 1327.*
Sedunov, J. 2016. What is the systemic risk exposure of financial institutions? *Journal of Financial Stability,* 24**,** 71-87.
Segoviano, M. A. & Goodhart, C. 2009. Banking stability measures. *IMF Working Paper No. 09/4*.
Sewraj, D., Gebka, B. & Anderson, R. D. J. 2018. Identifying contagion: A unifying approach. *Journal of International Financial Markets Institutions & Money,* 55**,** 224-240.
Shahzad, S. J. H., Hoang, T. H. V. & Arreola-Hernandez, J. 2019. Risk spillovers between large banks and the financial sector: Asymmetric evidence from Europe. *Finance Research Letters,* 28**,** 153-159.
Shefrin, H. & Statman, M. 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance,* 40**,** 777-790.
Shen, P.-L., Li, W., Wang, X.-T. & Su, C.-W. 2015. Contagion effect of the European financial crisis on China's stock markets: Interdependence and pure contagion. *Economic Modelling,* 50**,** 193-199.
Silva, W., Kimura, H. & Sobreiro, V. A. 2017. An analysis of the literature on systemic financial risk: A survey. *Journal of Financial Stability,* 28**,** 91-114.
Simkovic, M. 2013. Competition and crisis in mortgage securitization. *Indiana Law Journal,* 88**,** 213-272.
Sims, C. A. 1980. Macroeconomics and Reality. *Econometrica,* 48**,** 1-48.
Singh, D. R. A. 2009. ASEAN: perspectives on economic integration: ASEAN capital market integration: issues and challenges. *LSE Research Online Documents on Economics 43635*.

Sklar, M. 1959. Fonctions de repartition an dimensions et leurs marges. *Publ. inst. statist. univ. Paris,* 8**,** 229-231.
Soramäki, K. & Cook, S. 2013. SinkRank: An algorithm for identifying systemically important banks in payment systems. *Economics: The Open-Access, Open-Assessment E-Journal,* 7**,** 1-27.
Su, D. & Fleisher, B. M. 1998. Risk, return and regulation in Chinese stock markets. *Journal of Economics and Business,* 50**,** 239-256.
Summer, M. 2013. Financial contagion and network analysis. *Annual Review of Financial Econonomics,* 5**,** 277-297.
Syllignakis, M. N. & Kouretas, G. P. 2011. Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance,* 20**,** 717-732.
Tarashev, N. A., Borio, C. E. & Tsatsaronis, K. 2009. The systemic importance of financial institutions. *BIS Quarterly Review, September 2009*. Available at SSRN: https://ssrn.com/abstract=1473007.
Thomson, J. B. 2009. On systemically important financial institutions and progressive systemic mitigation. *DePaul Business and Commercial Law Journal,* 8**,** 135-150.
Tirole, J. 2011. Illiquidity and all its friends. *Journal of Economic Literature,* 49**,** 287-325.
Townsend, R. M. 1987. Economic organization with limited communication. *The American Economic Review,* 77(5), 954-971.
Umutlu, M., Akdeniz, L. & Altay-Salih, A. 2010. The degree of financial liberalization and aggregated stock-return volatility in emerging markets. *Journal of Banking & Finance,* 34**,** 509-521.
Upper, C. 2011. Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability,* 7**,** 111-125.
Upper, C. & Worms, A. 2004. Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review,* 48**,** 827-849.
Vallascas, F. & Keasey, K. 2012. Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful. *Journal of International Money and Finance,* 31**,** 1745-1776.
Vithessonthi, C. & Kumarasinghe, S. 2016. Financial development, international trade integration, and stock market integration: Evidence from Asia. *Journal of Multinational Financial Management,* 35**,** 79-92.
Wang, G.-J., Jiang, Z.-Q., Lin, M., Xie, C. & Stanley, H. E. 2018a. Interconnectedness and systemic risk of China's financial institutions. *Emerging Markets Review,* 35**,** 1-18.
Wang, G.-J., Xie, C., He, K. & Stanley, H. E. 2017. Extreme risk spillover network: application to financial institutions. *Quantitative Finance,* 17**,** 1417-1433.
Wang, G.-J., Xie, C. & Stanley, H. E. 2018b. Correlation Structure and Evolution of World Stock Markets: Evidence from Pearson and Partial Correlation-Based Networks. *Computational Economics,* 51**,** 607-635.
Wang, G.-J., Xie, C., Zhao, L. & Jiang, Z.-Q. 2018c. Volatility connectedness in the Chinese banking system: Do state-owned commercial banks contribute more? *Journal of International Financial Markets, Institutions and Money,* 57**,** 205-230.
Wang, K., Chen, Y.-H. & Huang, S.-W. 2011. The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach. *International Review of Economics & Finance,* 20**,** 654-664.

Wang, L. 2014. Who moves East Asian stock markets? The role of the 2007–2009 global financial crisis. *Journal of International Financial Markets, Institutions and Money,* 28**,** 182-203.
Wang, Y., Shan, X. & Geng, J. 2015. Estimating the Systemic Risk of China's Banking Industries Based on Merton Model. *Applied Mathematics & Information Sciences,* 9(2)**,** 957-964.
Wang, Z., Kutan, A. M. & Yang, J. 2005. Information flows within and across sectors in Chinese stock markets. *The Quarterly Review of Economics and Finance,* 45**,** 767-780.
Witt, S. F. & Witt, C. A. 1992. *Modeling and Forecasting Demand in Tourism,* London, London Academic Press.
Wu, F. 2019a. Sectoral contributions to systemic risk in the Chinese stock market. *Finance Research Letters,* 31**,** 386-390.
Wu, F. 2019b. Stock market integration in East and Southeast Asia: The role of global factors. *International Review of Financial Analysis,* doi.org/10.1016/j.irfa.2019.101416.
Wu, F., Zhang, D. & Zhang, Z. 2019. Connectedness and risk spillovers in China's stock market: A sectoral analysis. *Economic Systems,* doi.org/10.1016/j.ecosys.2019.100718.
Xu, Q., Chen, L., Jiang, C. & Yuan, J. 2018. Measuring systemic risk of the banking industry in China: A DCC-MIDAS-t approach. *Pacific-Basin Finance Journal,* 51**,** 13-31.
Yang, C., Xueshua, Z., Jiang, L., Hu, S. & Li, H. 2016. Study on the contagion among American industries. *Physica A: Statistical Mechanics and its Applications,* 444**,** 601-612.
Yang, R., Li, X. & Zhang, T. 2014. Analysis of linkage effects among industry sectors in China's stock market before and after the financial crisis. *Physica A: Statistical Mechanics and its Applications,* 411**,** 12-20.
Yao, S. J., He, H. B., Chen, S. & Ou, J. H. 2018. Financial liberalization and cross-border market integration: Evidence from China's stock market. *International Review of Economics & Finance,* 58**,** 220-245.
Yarovaya, L., Brzeszczyński, J. & Lau, C. K. M. 2016. Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis,* 43**,** 96-114.
Yarovaya, L. & Lau, M. C. K. 2016. Stock market comovements around the Global Financial Crisis: Evidence from the UK, BRICS and MIST markets. *Research in International Business and Finance,* 37**,** 605-619.
Yu, H., Fang, L., Sun, B. & Du, D. 2017. Risk contribution of the Chinese stock market to developed markets in the post-crisis period. *Emerging Markets Review,* 34**,** 87-97.
Yu, I.-W., Fung, K.-P. & Tam, C.-S. 2010. Assessing financial market integration in Asia – Equity markets. *Journal of Banking & Finance,* 34**,** 2874-2885.
Zawadowski, A. 2011. Interwoven lending, uncertainty, and liquidity hoarding. *Boston University School of Management Research Paper*, No.2011-13. https://ssrn.com/abstract=1786672 or http://dx.doi.org/10.2139/ssrn.1786672.
Zawadowski, A. 2013. Entangled financial systems. *The Review of Financial Studies,* 26**,** 1291-1323.
Zhang, B. & Li, X.-M. 2014. Has there been any change in the comovement between the

Chinese and US stock markets? *International Review of Economics & Finance,* 29**,** 525-536.
Zhang, D. 2017. Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. *Energy Economics,* 62**,** 323-333.
Zhang, D. & Broadstock, D. C. 2018. Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis,* 10.1016/j.irfa.2018.08.003.
Zhang, D. & Fan, G. 2018. Regional spillover and rising connectedness in China's urban housing prices. *Regional Studies,* 53**,** 861-873.
Zhang, D., Lei, L., Ji, Q. & Kutan, A. M. 2019. Economic policy uncertainty in the US and China and their impact on the global markets. *Economic Modelling,* 79**,** 47-56.
Zhang, D., Liu, Z., Fan, G.-Z. & Horsewood, N. 2017. Price bubbles and policy interventions in the Chinese housing market. *Journal of Housing and the Built Environment,* 32**,** 133-155.
Zhang, D., Shi, M. & Shi, X. 2018. Oil indexation, market fundamentals, and natural gas prices: An investigation of the Asian premium in natural gas trade. *Energy Economics,* 69**,** 33-41.
Zhang, Z. & Wu, F. 2019. Moral harzard, external governance and risk-taking: Evidence from commercial banks in China. *Finance Research Letters,* doi.org/10.1016/j.frl.2019.101383.
Zhao, X., Zhang, T. & Zhang, B. 2017. Research on the Risk Spillover Effect Between Financial Markets in China: Based on Dynamic CoES Model. *International Business and Management,* 15**,** 15-24.
Zheng, Z., Podobnik, B., Feng, L. & Li, B. 2012. Changes in cross-correlations as an indicator for systemic risk. *Scientific reports,* 2**,** 888. doi:10.1038/srep00888.
Zhou, C. 2010. Are banks too big to fail? Measuring systemic importance of financial institutions. *International Journal of Central Banking,* 6**,** 205-250.