Junhua Jiang

Essays on Financial Connectedness

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Tiivistelmä

Tämän väitöskirjan neljä esseetä tarkastelevat rahoitusmarkkinoiden linkittyneisyyksiä eri näkökulmista. Ensimmäisessä esseessä tutkitaan, että miten kiinteistömarkkinoiden subprime-kriisi ja Euroopan velkakriisi vaikuttivat Pohjoismaisten osakemarkkinoiden linkittyneisyyteen. Esseessä erotetaan osakkeiden diskonttokoron uutiskomponentin ja kassavirran uutiskomponentin vaikutukset linkittyneisyyteen. Tulokset osoittavat, että näiden kahden kriisin aikana ainoastaan subprime-kriisi voimisti Pohjoismaisten osakkeiden diskonttokoron ja kassavirran uutiskomponentin linkittyneisyyttä. Väitöskirjan toinen essee tutkii kiinteistöyhtiöiden ja rahoitussektorin osakkeiden volatiliteetin linkittyneisyyttä Kiinan osakemarkkinoilla. Suhteellisen osakemarkkinoiden volatiliteetin linkittyneisyyden perusteella voidaan todeta, että etenkin kiinteistö-yrityksen koosta riippuu niiden järjestelmävaikutus pankkisektorille.

Kolmas essee tarkastelee osakemarkkinoiden eri toimialojen linkittyneisyyttä. Tulokset osoittavat, että pankki- ja kiinteistösektori ovat suurimpia volatiliteettishokin vastaanottajia, kun taas rakennus- ja materiaali-, teollinen kuljetus ja kemikaalisektorit ovat shokkien lähettäjiä. Väitöskirjan neljäs essee tutkii Kiinan kiinteistömarkkinoiden säännöstelypolitiikan vaikutuksia kiinteistö- ja pankkisektorin linkittyneisyyteen. Tulokset osoittavat, että kiinteistötaloutta tukevat poliittiset toimet lisäävät kiinteistöosakkeiden kassavirtojen linkittyneisyyttä pankkiosakkeille ja suurin osa tästä vaikutuksesta tulee verokevennyksien tyyppisistä päätöksistä.

Asiasanat

Rahoitusmarkkinoiden linkittyneisyys, toimialojen linkittyneisyys, volatiliteetin siirtyminen, kiinteistömarkkinoiden säännöt, kiinteistömarkkinoiden riskit, pankit

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Abstract

This thesis analyzes financial connectedness from different perspectives in four essays. The first essay studies whether the subprime mortgage crisis and European debt crisis intensified the connectedness effect on the Nordic equity markets. The essay distinguishes between the connectedness effect of the discount rate news component and that of the cash flow news component of equity market returns. The results show that for the two financial crises, only the subprime mortgage crisis strengthened the connectedness effect of the discount rate news component and that of the cash flow news component on the Nordic equity markets. The second essay examines the equity volatility connectedness across China's real estate firms and financial institutions. Based on the relative level of equity volatility connectedness, the results indicate that size plays an important role in determining the systemic importance of a real estate firm to the banking sector.

The third essay analyzes the frequency connectedness of equity volatilities across different Chinese industries. The results show that the main receivers of volatility shocks in China are banking industry and real estate industry, while the main transmitters of volatility shocks are the industries of construction and materials, industrial transportation, and chemicals. The fourth essay examines the impact of real estate regulatory policies on the connectedness from the sector of real estate firms to the sector of banks in the case of China. The results indicate that real estate stimulating policies increase the cash flow connectedness of real estate firms to banks, with the effects mainly coming from tax-related stimulating policies.

Keywords

Financial Connectedness, Industry Connectedness, Contagion, Volatility Spillovers, Real Estate Regulations, Real Estate Risks, Banks

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Vaasa, March 2020

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1 INTRODUCTION

This doctoral dissertation examines financial connectedness from different perspectives. In particular, the first essay of the dissertation examines equity market connectedness, the second essay studies individual company connectedness, and the last two essays of the dissertation analyze industry connectedness. Connectedness refers to the connections of variables in a network or system. It is synonymous with interdependence or linkages. “Connectedness” and “spillover” can be used interchangeably in this dissertation (see Diebold & Yilmaz 2012, 2014). Another related concept is financial market integration studying the inter-relationships of financial markets. In contrast to the concept of financial market integration, financial connectedness emphasizes a network or system view and involves inter-relationships or connections at various levels, which can be pairwise connections between two variables or system-wide connections among all the variables in the system.

The dissertation contains four essays. The first essay studies whether the subprime mortgage crisis and European debt crisis intensified the connectedness or spillover effect on the Nordic equity markets, where the intensified connectedness effect is defined as contagion (see section 5 for various definitions of contagion). The second essay examines the equity volatility connectedness across the major real estate firms, banks, and other financial institutions in China. The third essay analyzes the frequency connectedness of equity volatilities across different industries in China. The fourth essay investigates whether real estate regulatory policies decrease the connectedness from the sector of real estate firms to the sector of banks in the case of China, where connectedness from the sector of real estate firms to the sector of banks is used to represent the real estate risks to the banking industry.

Connectedness is an essential concept in finance. For instance, connectedness plays a significant role in risk management, portfolio allocation, business-cycle analysis, and real-time crisis monitoring (Diebold & Yilmaz 2015). The risk of a portfolio depends on both the risk of individual assets and the connectedness among the assets. The benefits of portfolio diversification decrease with the level of connectedness among the assets. Time-varying connectedness implies time-varying portfolio risk and diversification benefits. Connectedness is generally high during financial crises, leading to low diversification benefits. In addition to the portfolio risk, another common type of risk is systemic risk. The level of systemic risk of a financial system could be determined by the extent of system-wide connectedness of the system. One determinant of the systemic risk contribution of a financial institution is its level of connectedness with the rest of the financial system. Due to financial market connectedness, financial risks also spread from one country to another. The speed and strength of risk transmissions largely depend on the level of connectedness across the financial markets in different countries.

This dissertation mainly focuses on the financial connectedness in the case of China. The case of China is interesting for the following reasons. Firstly, after decades of rapid economic growth, China has become the second largest global economy by nominal GDP and the largest global economy by purchasing power parity. The growth of the Chinese economy contributes significantly to the world economic growth. The status of the Chinese manufacturing and industrial output is viewed as a barometer of the world economy, affecting global equity, commodity, and currency markets (Baum, Kurov & Wolfe 2015).

Secondly, the second and fourth essays of the dissertation study the connectedness between the real estate industry and banking industry in China. The subprime mortgage crisis indicates that financial risks related to the real estate industry in the US can spread to the other industries and further affect the global financial and economic stability. Similarly, real estate industry in China shows large credit risk spillovers to the other industries and contributes a significant part of the total economic output; in addition, China's real estate loans and real estate investment account for a large part of the total bank loans and total fixed asset investment, respectively (Chan, Han & Zhang 2016). Hence, given the significance of the real estate industry in China and the gradually increasing importance of the overall Chinese economy, China’s real estate industry could also have significant implications for the global financial and economic stability. Moreover, compared to the real estate market in the US, Chinese real estate market has some distinct features: dramatic housing price growth, large total construction of floor space, high vacancy rates, and large control over the price and construction by the public sector (Glaeser et al. 2017). Chinese banks, on the other hand, are important part of the world banking sector. After the subprime crisis, global systemically important banks shifted from the developed economies to the emerging economies, particularly China (Alessandri, Masciantonio & Zaghini 2015). Financial Stability Board publishes a list of global systemically important banks each year since 2011. In their 2018 list of global systemically important banks, 4 out of the 29 banks are Chinese banks.

The remainder of this introductory chapter proceeds as follows. Section 2 describes the contribution of the dissertation. Section 3 presents the theoretical background on portfolio diversification, equity market integration, and financial contagion.[4] Section 4 reviews the financial connectedness methods and empirical applications of the methods. Section 5 summarizes the four constituent essays of the dissertation. Finally, section 6 presents the concluding remarks and implications of the dissertation.

[4] The concepts of portfolio diversification, equity market integration, and financial contagion are related to one another and to the idea of financial connection. The extent of market integration and the occurrence of financial contagion affect the potential gain from international portfolio diversification. Portfolio diversification activities across countries could make international equity markets more integrated, and international portfolio rebalancing following a financial crisis may raise the speed and severity of financial contagion. Finally, the degree of financial connections determines the potential benefits of portfolio diversification and the extent of market integration, while changes in the level of financial connections following a financial crisis are signs of financial contagion.

2 CONTRIBUTION OF THE DISSERTATION

The dissertation investigates financial asset connectedness from different angles in four essays. The first essay examines connectedness of equity markets and the impact of financial crises on equity market connectedness. The second essay studies equity volatility connectedness of individual companies. The third and the fourth essays analyze connectedness at the industry level. In addition, the fourth essay also reveals the effect of regulatory policies on the dynamic connectedness.

The dissertation enriches the understanding of financial connectedness and factors affecting it. In addition to the main contribution to the literature on financial connectedness, the dissertation also contributes to other strands of literature on financial contagion, systemic risk, risk measurement, risk monitoring, and real estate regulation.[5] Generally, the dissertation, falling under the theme of financial connectedness, integrates several lines of literature and provides new insights into each of them.

Specifically, the first essay of the dissertation examines the shifting of equity market connectedness due to the occurrence of financial crises. This essay defines contagion as the intensified connectedness/spillover effect during crisis period relative to tranquil period. Extensive research has been conducted on equity market contagion (e.g., Forbes & Rigobon 2002; Baur 2012; Bekaert et al. 2014). However, previous research has focused on the overall contagion effect, i.e., the contagion effect of the overall shocks to equity returns in the crisis-hit country on the equity returns in other countries. Separating the overall shocks to equity returns into a discount rate news component and a cash flow news component by the framework of Campbell (1991), the essay studies the contagion effect of the subprime mortgage crisis and European debt crisis arising from each of these two return components. The discount rate news component reflects changes in investors' expectation of future discount rates, while the cash flow news component reflects changes in investors' expectation of future dividends. Distinguishing between contagion effect of the discount rate news component and that of the cash flow news component deepens our understanding of the underlying characteristics of the financial crises. Moreover, instead of using correlation coefficients that may be biased upward during financial crises due to the impact of high volatilities (Forbes & Rigobon 2002), the essay utilizes the spillover measures of Diebold and Yilmaz (2012), which already take into account the impact of total variations (Diebold & Yilmaz 2015).

[5] More specifically, the first essay contributes to the literature on financial contagion; the second and the third essays provide insights into the issues of systemic risk, risk measurement, and risk monitoring; the fourth essay contributes to the literature on real estate regulation.

The second essay of the dissertation studies the dynamic equity volatility connectedness across the major real estate firms, banks, and other financial institutions in the case of China. The essay complements previous research on the volatility connectedness of financial institutions in the developed economies (e.g., Diebold & Yilmaz 2014, 2016). The essay also provides an intuitive way to measure the systemic importance of a real estate firm to the banking sector and that of a bank to the financial system, based on the relative level of equity volatility connectedness. Furthermore, previous studies on systemic importance of financial institutions document the average and changes of the average rankings of systemic importance over different time periods (e.g., Huang, Haan & Scholtens 2019; Huang et al. 2016). The essay is the first to systematically analyze the transition behavior of the systemic importance rankings of real estate firms and banks by discrete time Markov Chain model.

The third essay of the dissertation examines frequency volatility connectedness across different industries in China. This essay contributes to the literature in the following ways. Firstly, the essay is the first to explore the frequency volatility connectedness across different industries by the advantageous method of Barunik and Krehlik (2018). The frequency connectedness method of Barunik and Krehlik (2018) can be used to show whether the connectedness arises from the short-, medium-, or long-term impact of shocks, which may be important for risk management, portfolio allocation, and monitoring of financial risks. Secondly, the essay complements previous research on the connectedness among assets in China, which received relatively less attention in the previous literature. Thirdly, the essay reveals the underlying frequency sources of volatility connectedness and systemic risk during important sub-periods, such as periods of subprime crisis and European debt crisis.

The fourth essay of the dissertation studies whether real estate regulatory policies can constrain real estate risks to banks in the case of China. The essay uses the return and return component connectedness from the sector of real estate firms to the sector of banks to represent the real estate risks to banks. Previous research has evaluated the effects of regulatory policies on restraining real estate prices (e.g., Vandenbussche, Vogel & Detragiache 2015; Kuttner & Shim 2016; Jang, Song & Ahn 2020), but neglected the issue of whether regulatory policies can constrain real estate risks, particularly real estate risks to banking sector. The essay argues that it could be more desirable to examine the effects of regulatory policies on constraining the real estate risks, rather than real estate prices. On the one hand, it is challenging to determine whether real estate prices are too high or whether real estate bubbles exist (Ahuja et al. 2010; Cadil 2009). On the other hand, there are bad real estate price booms and good real estate price booms: bad real estate price booms are real estate bubbles and require policy actions, while good real estate price booms are benign and policy actions could unnecessarily restrict credit (Crowe et al. 2013).[6] Thus, real estate regulatory policies constraining good real estate price booms are not necessarily "effective". In contrast, high real estate risks are always undesirable and regulatory policies reducing real estate risks would be more practical.

[6] According to Crowe et al. (2013), bad real estate price booms are real estate bubbles, i.e., price misalignments in relation to economic fundamentals; good real estate price booms are not real estate bubbles, but only large or rapid movements in real estate prices.

3 THEORETICAL BACKGROUND

3.1 Portfolio diversification

The “expected returns–variance of returns” rule of Markowitz (1952) suggests that investors should choose portfolios with the highest expected return for a given level of variance (or the lowest variance for a given level of expected return). After the seminal work of Markowitz, later research develops alternative portfolio theories that consider higher moments of the distribution of portfolio returns (Lee 1977), multi-period investment (Hakansson 1974), and continuous-time analysis (Merton 1990). Later research also takes into account more realistic investor problems, such as borrowing constraint (Fu, Lari-Lavassani & Li 2010) and infrequently traded stocks (Castellano & Cerqueti 2014). However, the mean-variance theory of Markowitz remains the cornerstone of modern portfolio theory (Elton & Gruber 1997).

For a given level of expected return, the variance of a portfolio could be substantially lower than that of the constituent assets: the lower the correlations among the constituent assets, the higher the diversification benefits. For a well-diversified portfolio, the unsystematic risks can be fully diversified away. Consequently, only the non-diversifiable systematic risks matter for investors. Unsystematic risks are asset-specific risks affecting a single asset, while systematic risks are market-wide risks affecting all the assets. Compared to assets in the same country, the benefits of diversification are even larger when assets in different countries are included in one portfolio, since assets in different countries have relatively lower correlations. International diversification is profitable, if expected return on foreign securities satisfies the following condition:

(1) $$\overline{R}_F - R_f > (\overline{R}_D - R_f)({}^{\sigma_F}/_{\sigma_D}\,\rho),$$

where R_f is the risk-free rate. $\overline{R}_F$ is the expected return on the foreign securities denominated in domestic currency, and $\overline{R}_D$ is the expected return on the domestic securities. σ_F and σ_D are the corresponding standard deviation of the foreign securities and domestic securities, respectively. ρ is the return correlation coefficient between the foreign and domestic securities (Elton et al. 2011: 219–222.).

Equation 1 shows that to make the international diversification profitable, the minimum requirement for $\bar{R}_F - R_f$ is $(\bar{R}_D - R_f)(^{\sigma_F}/_{\sigma_D}\,\rho)$. This value is smaller than $(\bar{R}_D - R_f)$, if $^{\sigma_F}/_{\sigma_D}\,\rho < 1$. In other words, as long as $^{\sigma_F}/_{\sigma_D}\,\rho < 1$, international diversification is profitable even when the expected return on the foreign securities is smaller than that on the domestic securities. Equation 1 also suggests that international diversification opportunities depend on ρ and the relative values of σ_F and σ_D. For a US investor investing in the developing markets, he or she may face relatively larger σ_F but smaller ρ, as developing markets tend to have higher volatilities but lower correlations with the US market.

Empirical evidence on the benefits of international portfolio diversification is extensive. For instance, Grubel (1968) provides some early evidence on the benefits of diversifying in the international stock markets. Solnik (1974) shows that portfolio risks can be significantly reduced when the investment opportunity set is expanded from US stocks to international stocks. Jorion (1989) finds similar results when the investable assets include both stocks and bonds. Liu (2016) finds that diversification with international corporate bonds reduces risks and increases risk-adjusted returns. The four studies mentioned above analyze the benefits of international diversification from the perspective of US investors. Driessen and Laeven (2007) examine international diversification from the angle of local investors. Their study suggests that investors, especially those in the developing countries, benefit from international diversification. Furthermore, recent studies reveal that international diversification with bitcoin reduces portfolio risks (Briere, Oosterlinck & Szafarz 2015; Guesmi et al. 2019). Despite the extensive evidence of substantial gain from international diversification, the occurrence of financial crises, the development of information technology, and the general trend of globalization could contribute to diminishing international diversification benefits.

3.2 Equity market integration

Previous literature proposes three definitions of financial market integration (Kearney & Lucey 2004). One definition invokes the law of one price and suggests that as a result of unrestricted international capital flows, interest rates across countries should be equal (or more generally, international financial assets with identical risks should have equal rates of return). Another definition of financial market integration is based on the study of Stockman (1988), according to which financial integration is perfect if the set of international financial markets enables market participants to insure against the full set of anticipated states of nature. The third definition of financial market integration is related to the degree of domestic investment financed by world savings: for perfectly integrated capital markets, the correlation between domestic investment and savings should be small (Feldstein & Horioka 1980).

There is no generally accepted method to properly measure the extent of equity market integration (Pukthuanthong & Roll 2009). Previous studies measure equity market integration by both return-based and quantity-based indicators (Adam et al. 2002). Quantity-based indicators build on quantities such as the size of international capital flows and the composition of portfolios. Previous research applies various methods to examine the degree of equity market integration: international CAPM, correlation or cointegration structure of markets, and time-varying measures of integration (Kearney & Lucey 2004). For instance, Pukthuanthong and Roll (2009) propose an alternative integration measure based on the adjusted R-square of a multi-factor model. Bekaert et al. (2011) introduce an integration/segmentation measure using the difference between local and global industry valuation ratios. Bekaert and Mehl (2019) measure market integration by the conditional betas of an international factor model. Each measurement of integration has its own strengths and weakness, and some measurements generate very similar long-run integration pattern (Billio et al. 2017). For example, despite of its simplicity, correlation coefficient is a flawed measure of integration, since correlation between two markets can be very small even when they are perfectly integrated (Pukthuanthong and Roll 2009).

A wide range of factors affect the extent of equity market integration. For instance, capital market liberalization, capital account openness, trade openness and structure, and equity market openness are important contributing factors of equity market integration (Bekaert & Harvey 2000; Quinn & Voth 2008; Chambet & Gibson 2008; Eiling & Gerard 2015). There is also evidence that bilateral foreign direct investment, exchange rate volatility, and equity market capitalization influence market integration (Shi et al. 2010; Johnson & Soenen 2003; Buttner & Hayo 2011). In addition, financial development of a country also affects its integration with the global equity market (Vithessonthi & Kumarasinghe 2016). Other determinants of equity market integration include geographical variables and cultural distance (Flavin, Hurley & Rousseau 2002; Lucey & Zhang 2010).

Increasing financial integration in recent years has important implications. The complete market definition of integration suggests that higher degree of integration provides better insurance against possible future states of nature for the market participants. Increasing market integration also implies declining diversification benefits of international portfolios. Furthermore, increasing market integration raises the robustness of the economies and destabilizes the household savings rates (Kearney & Lucey 2004).

3.3 Financial contagion

Global financial markets and economy were significantly affected by the Asian financial crisis in the 1990s, after which the issue of financial contagion caught the attention of policymakers and economists (Dornbusch, Park & Claessens 2000). In spite of the importance of financial contagion, there is no consensus on the definition of the term. Pericoli and Sbracia (2003) list five most representative definitions in the previous literature. Contagion occurs if any of the following situations were true: given that a crisis occurred in one country, the probability of a crisis in another country is significantly higher; asset price volatilities spread from the crisis country to non-crisis countries; there are comovements of asset prices across countries that cannot be attributed to fundamentals; following a crisis in one market or group of markets, comovements of prices and quantities across markets are significantly higher; in response to a shock in one market, the transmission channel strengthens or weakens (Pericoli & Sbracia 2003).

A variety of methods have been used to measure contagion. For instance, Forbes and Rigobon (2002) test for equity market contagion by a correlation measure corrected for market volatility. Bekaert et al. (2014) analyze equity market contagion based on the factor loadings and residual correlations of an international factor model. Forbes (2012) divides the methods for measuring contagion into five categories: probability analysis, cross-market correlations, VAR models, latent factor/GARCH models, and extreme value analysis. There are both advantages and disadvantages for each of these methods (see Forbes 2012). The approach by probability models is in line with the first definition of contagion in Pericoli and Sbracia (2003), while the latent factor/GARCH models are consistent with their second and third definitions of contagion. Dungey et al. (2005) provide a review of methodologies for measuring contagion. They point out that the way in which information (asset returns) is used to identify contagion largely distinguishes alternative empirical models of contagion.

Regarding the causes of contagion, Dornbusch, Park and Claessens (2000) identify two categories: fundamental causes and investors' behavior. The first category emphasizes transmission of shocks across countries as a result of their real and financial linkages. The second category is related to the behavior of investors or other financial agents, rather than the fundamentals. Fundamental causes include common shocks, financial links, and trade links and competitive devaluations.

Investors' behavior involves issues such as liquidity and incentive problems and changes in the rules of the game. Similar to the study of Dornbusch, Park and Claessens (2000), Schmukler, Zoido, and Halac (2003) suggest three broad channels of contagion: real links, financial links, and herding behavior.

4 FINANCIAL CONNECTEDNESS

To measure financial connectedness, the dissertation utilizes the framework of Diebold and Yilmaz (2009, 2012, 2014) and Barunik and Krehlik (2018).[7] Diebold and Yilmaz (2009) propose a spillover index to measure the linkages in asset returns and volatilities. The spillover index aggregates the cross variance shares of a forecast-error variance decomposition from a VAR model. Extending the spillover index of Diebold and Yilmaz (2009), Diebold and Yilmaz (2012) introduce measures of both total spillovers and directional spillovers based on the generalized forecast-error variance decompositions, which is invariant to the orderings of variables in the VAR model. Diebold and Yilmaz (2014) interpret the forecast-error variance decompositions as weighted, directed networks and argue that the spillover measures provide a natural and insightful way to quantify the connectedness at a variety of levels. Diebold and Yilmaz (2014) show that their connectedness measures are closely related to the measures of network connectedness and systemic risk.

Barunik and Krehlik (2018) notice that at different frequencies, shocks to economic activity could have different impact. Thus, they consider cross variance shares of forecast-error variance decompositions at various frequency bands. They propose two types of connectedness measures: within connectedness and frequency connectedness. The within connectedness quantifies the connectedness within a specific frequency band. The frequency connectedness, in contrast, also takes into account the share of forecast-error variance at the given frequency band. The sum of the frequency connectedness over all (disjoint) frequency bands gives the original connectedness of Diebold and Yilmaz (2014). Hence, frequency connectedness can be used to examine the underlying frequency sources of connectedness.

The above connectedness or spillover methods have been widely applied for analyzing financial or economic connectedness. Diebold and Yilmaz (2009) study the return and volatility connectedness of 19 equity markets and reveal the divergent patterns of dynamic return and volatility connectedness. Diebold and Yilmaz (2012) examine the volatility connectedness across four US asset classes (stocks, bonds, foreign exchange, and commodities). They show that the global

[7] Kara, Tian, and Yellen (2015) separate the empirical measures of interconnectedness into two categories: network approaches and non-network approaches. The methods employed in the dissertation are network approaches (for other network approaches and non-network approaches, see Kara, Tian, & Yellen 2015 and the references therein). The employed network approaches provide a "unified framework for conceptualizing and empirically measuring connectedness at a variety of levels, from pairwise through system-wide" (Diebold & Yilmaz 2014).

financial crisis of 2007-2009 increased the connectedness among the assets, particularly the connectedness from stocks to the other assets. Diebold and Yilmaz (2014) analyze the equity volatility connectedness of major financial institutions in the US, and Diebold and Yilmaz (2016) extend the analysis to include major financial institutions in Europe as well. Diebold and Yilmaz (2015) provide a comprehensive analysis of financial and macroeconomic connectedness (such as the connectedness among assets across countries and the connectedness of global real economic activity).

Barunik and Krehlik (2018) characterize the frequency dynamics of equity volatility connectedness among US financial institutions. Focusing on the volatility connectedness among four global asset classes, Tiwari et al. (2018) find that at the highest frequency, stocks and sovereign bonds are the net transmitters of volatility, and at lower frequencies, the other two asset classes (CDS and foreign exchange) become the net transmitters of volatility. Wang and Wang (2019) investigate the frequency dynamics of volatility connectedness between crude oil and 11 sectoral stock markets in China. Their study shows that oil market is mainly a short-term volatility transmitter to the Chinese stock markets. Similarly, the study by Ferrer et al. (2018) also shows the importance of short-term component for the frequency dependent connectedness between crude oil prices and US renewable energy stocks. Other studies have also used the aforementioned methodology for evaluating the connectedness of banks (Demirer et al. 2018; Wang et al. 2018), stock and precious metal markets (Mensi, Al-Yahyaee & Kang 2017), international real estate investment trusts (Liow & Huang 2018), cryptocurrency markets (Yi, Xu & Wang 2018; Gillaizeau et al. 2019; Ji et al. 2019), international economic policy uncertainty (Klobner & Sekkel 2014; Luk et al. 2018), seafood markets (Dahl & Jonsson 2018), and so on.

5 SUMMARY OF THE ESSAYS

This section briefly describes the four constituent essays of the dissertation. The individual contribution of the co-authors for each essay is listed below:

Essay 1: This essay is single-authored by Junhua Jiang.

Essay 2: Junhua Jiang is responsible for collecting the data, analyzing the data, writing the essay, and revising the essay. Dr. Äijö contributed comments and suggestions for improving the essay.

Essay 3: Dr. Tiwari is responsible for writing the methodology part, providing comments for improving the essay, and giving advices for revising the essay. Dr. Äijö and Dr. Piljak are responsible for writing part of the Introduction section and offering comments for improving the essay. Junhua Jiang collected and analyzed the data. Junhua Jiang is also responsible for writing part of the Introduction section, Data and method section, Results section, and Conclusions. Dr. Äijö, Dr. Piljak, and Junhua Jiang revised the essay and drafted the response letters to the reviewers.

Essay 4: This essay is single-authored by Junhua Jiang.

5.1 Discount rate or cash flow contagion? Evidence from the recent financial crises

The first essay of this dissertation investigates whether the subprime mortgage crisis and European debt crisis strengthened the spillover or connectedness effect on the Nordic (Denmark, Finland, Norway, and Sweden) equity markets. In particular, utilizing the vector autoregressive framework of Campbell (1991), the essay first decomposes the aggregate equity market returns of the two crisis-originating countries (US and Greece) into a discount rate news component and a cash flow news component. The essay then examines the spillover effect of the two return components on the Nordic equity markets by the spillover indexes of Diebold and Yilmaz (2012). The essay refers to the intensified spillover effect of the discount rate news component (cash flow news component) during a crisis period relative to the pre-crisis period as discount rate contagion (cash flow contagion).

The data used in this study include monthly equity market indexes for US(S&P500), Greece (FTSE index), Germany (DAX30), and the four Nordic countries (MSCI indexes for Denmark, Finland, Norway, and Sweden).[8] The sample of data also include the dividend yield for the Greek and US equity market indexes, total return indexes for the Greek small growth stocks and small value stocks (MSCI index), monthly returns on the US small growth stocks and small value stocks, and 3-month and 10-year government bond rates for Greece and US. The sample period is divided into three sub-periods: pre-crisis period (Jan. 2004-Jun. 2007), subprime mortgage crisis period (Jul. 2007-Dec. 2009), and European debt crisis period (Jan. 2010- Dec. 2012).

The study finds that the subprime mortgage crisis shows both discount rate and cash flow contagion effect on the Nordic equity markets, with the effect of the discount rate contagion being more significant. In other words, expectations of higher future discount rates and lower future corporate earnings due to the occurrence of the subprime crisis spread to the Nordic markets, with the effect of the former being more pronounced. On the other hand, the European debt crisis does not exhibit either discount rate or cash flow contagion effect on the Nordic markets. However, during the European debt crisis, spillovers among the German, US, and Nordic equity markets become stronger, and expectations of lower future cash flows due to the occurrence of the sovereign debt crisis appear to spread to the Finnish market.

5.2 Equity volatility connectedness across China's real estate firms and financial institutions

The second essay of this dissertation analyzes the equity volatility connectedness among the major Chinese real estate firms, banks, and other financial institutions. Built on the relative level of equity volatility connectedness, the essay also examines the systemic importance of each real estate firm to the banking sector and that of each bank to the financial system. Since real estate loans account for a large part of the total bank loans in China, real estate sector is essential for the banking sector. Furthermore, as a crucial part of the financial system, banking sector in China provides the most important source of financing for the business operations.

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[8] Since DAX30 index is a more commonly used equity market index for Germany, the study uses the DAX30 index (instead of the MSCI index) for representing the German equity market. Although DAX30 index and MSCI index for Germany may have different selection criteria, the impact of the different selection criteria on the spillover effect should be the same over the pre-crisis period and crisis period. As the study determines the contagion effect by comparing the spillover effect during the pre-crisis period and crisis period, the different selection criteria for the DAX30 and the MSCI indexes are unlikely to affect the main results of the study.

The sample of companies analyzed in the essay contains 7 real estate firms, 10 banks, 3 broker-dealer firms, and 2 insurance firms that are listed on the two stock exchanges in Mainland China. To compute the daily realized volatility, the essay uses the daily high, low, opening and closing stock prices of these companies from 2 September 2010 to 18 December 2015. The essay evaluates the volatility connectedness by the method of Diebold and Yilmaz (2014) and analyzes the transitions of systemic importance rankings by discrete time Markov Chain model.

The essay shows that total directional connectedness from real estate firms to banks weakens over the sample period, whereas total directional connectedness from banks to real estate firms and that from banks to the financial institutions become stronger. This finding implies that despite widespread worries about potential real estate bubbles in China, market participants are more concerned about the risks from the banking sector than those from the real estate sector over the sample period. The essay also finds that on the one hand, the largest real estate firms display the highest systemic importance to the banking sector, and it takes the least time for them to transit from a low systemic importance ranking to a high systemic importance ranking. On the other hand, medium-sized banks demonstrate higher systemic importance to the financial system than the largest banks. The largest bank (Industrial and Commercial Bank of China) has the highest probability of being the least or second least systemically important bank in the long run, and it takes the least time to return to the status of least systemically important bank whenever it is not.

5.3 Frequency volatility connectedness across different industries in China

The third essay of the dissertation studies the dynamic frequency connectedness of equity volatilities across different industries in China. This empirical study employs the frequency connectedness method of Barunik and Krehlik (2018).[9] Frequency connectedness can be used to show the underlying frequency sources of connectedness, i.e., whether the connectedness arises due to short-, medium- or long-term impact of shocks. This is an important issue, since different agents may be concerned with different levels of connectedness at different frequencies. For instance, short-term investors could be concerned with the pairwise connectedness between industries at high or medium frequencies, while policy

[9] This study only examines the financial linkage of various Chinese industries by the frequency connectedness method of Barunik and Krehlik (2018). Chan, Han and Zhang (2016) use the method of input-output analysis of the real economy to evaluate the real linkage between the real estate sector and other sectors in China.

makers may be interested in the system-wide connectedness among the industries at low frequencies.

The sample of industries included in the analysis are Mining, Auto and Parts, Chemicals, Electricity, Construction and Materials, General Retailers, Industrial Transportation, Software and Computer Services, Banks, Real Estate, Health Care, and Media. Except for the Real Estate industry, the selected industries are the FTSE CHINA 600 industries in Datastream that match the industry classifications of listed firms by China Securities Regulatory Commission. The Real Estate industry is represented by the Shenzhen Real Estate equity index. Daily high, low, opening, and closing equity price indexes of the analyzed industries from October 2003 to April 2018 were collected from Datastream. The study uses frequency bands up to 1 week, 1 week to 1 month, and 1 month to 1 year to measure the high (or short-term), medium (or medium-term), and low frequency (or long-term) connectedness, respectively.

The sample period of the study is divided into five sub-periods based on the Bai-Perron test (Bai and Perron 1998) on the overall Diebold and Yilmaz connectedness among the industries. The first sub-period (26.10.2004-18.4.2007) is the period before the Global Financial crisis; the second sub-period (19.4.2007-25.1.2011) corresponds to the Global Financial Crisis period; the third sub-period (26.1.2011-19.2.2013) corresponds to the European debt crisis period; the last two sub-periods (20.2.2013-7.4.2015 and 8.4.2015-30.4.2018) are the periods after the financial crises. Before the Global Financial Crisis, Banking industry in China was the main receiver of volatility connectedness at medium and low frequencies; however, at high frequencies, Media and Real Estate industries became the main receivers of volatility connectedness or targets of risks. During the Global Financial Crisis, Banking industry and Real Estate industry were the main targets of risks at all frequency levels, and Chemicals was the major transmitter of volatility connectedness (or source of risks) at high frequencies. During the European debt crisis, Banks and Real Estate were still the main targets of risks. The main sources of risks over the fourth sub-period were Construction and Materials and Chemicals, while the main target of risks among the industries during the last sub-period was Banking industry.

5.4 Can real estate regulatory policies constrain real estate risks to banks? Evidence from China

The fourth essay of the dissertation examines whether the real estate regulatory policies issued by the policy makers in China can reduce the connectedness from the sector of real estate firms to the sector of banks. More specifically, the study first decomposes the unexpected excess equity returns on the sector of the real estate firms into a discount rate news component and a cash flow news component by the framework of Campbell (1991). The study then investigates whether the real estate regulatory policies can reduce the overall return connectedness, discount rate news component connectedness, or cash flow news component connectedness from the sector of real estate firms to the sector of banks. In the study, the overall return connectedness, discount rate news component connectedness, and cash flow news component connectedness are used to represent the overall risks of the real estate firms to banks, the discount rate risks of the real estate firms to banks, and the risks of the real estate market to banks, respectively.

The data of the study contain equity indexes for the sector of real estate firms (China A-Datastream Real Estate index), the sector of banks (China A-Datastream Banks index), small growth stocks (MSCI China index), and small value stocks (MSCI China index). The data also include dividend yields of the China A-Datastream Real Estate index, 3-month and 10-year government bond yields, and market values and stock prices of the companies that are constituents of the SSE 50 index (excluding the real estate firms and banks). The sample period of the study is separated into three "controlling" and two "stimulating" sub-periods. The objective of real estate regulatory policies issued during a controlling period is to stabilize or slow the growth of the housing prices, and the corresponding regulatory policies are referred to as controlling policies; the objective of real estate regulatory policies issued during a stimulating period is to support or stimulate the real estate market, and the corresponding regulatory policies are referred to as stimulating policies. In addition, the study also distinguishes between four types of real estate regulatory policies: financial policies, tax policies, land policies, and industrial policies.

The study shows that real estate stimulating policies increase the risks of the real estate market to banks, with the effects mainly coming from tax-related stimulating policies. Two types of real estate control policies affect the discount rate risks of the real estate firms to banks: financial control policies raise the discount rate risks of the real estate firms to banks, whereas industrial control policies reduce the discount rate risks of the real estate firms to banks. Two types of real estate control policies and two types of real estate stimulating policies affect the overall risks of the real estate firms to banks. Industrial control policies and tax stimulating policies increase the overall risks of the real estate firms to banks; land control policies and financial stimulating policies reduce the overall risks of the real estate firms to banks.

6 CONCLUDING REMARKS AND IMPLICATIONS

The thesis studies financial connectedness in four interconnected essays, with an emphasis on the connectedness of equity returns (including return components) and volatilities. The first and the fourth essays examine the connectedness between equity returns and return components: the first essay emphasizes the impact of financial crises on the connectedness, while the fourth essay focuses on the role of real estate regulatory policies in the connectedness dynamics. The second and the third essays investigate the connectedness of equity volatilities, focusing on risk measurement and monitoring.

The two equity return components, discount rate news component and cash flow news component, reflect changes in investors' expectation of future discount rates and changes in expectation of future dividends, respectively. One may note that discount rates (cost of capital) are more likely to be affected by monetary policies through risk-free rates, whereas dividends are more likely to be influenced by fiscal policies (such as corporate income taxes, which affect net corporate earnings and hence dividend payments). The first essay of the thesis shows that the subprime mortgage crisis has contagion effect from both the discount rate news component and cash flow news component of equity returns. There is also some evidence that following the sovereign debt crisis, expectations of lower future cash flows spread to the Finnish market. Therefore, to counter the impact of the subprime mortgage crisis, both monetary and fiscal policies are needed; to mitigate the influence of the sovereign debt crisis on the Finnish market, fiscal policies may be more crucial.

The fourth essay studies the connectedness from the sector of real estate firms to the sector of banks and the role of real estate regulatory policies in the connectedness dynamics. The "products" of real estate firms are the houses. In consequence, housing prices largely determine the earnings or dividends of real estate firms. Hence, the essay uses the connectedness from the cash flow news component of real estate firms to banks to proxy for the risk of housing price changes to banks. The essay finds that real estate control policies issued in China do not seem to be able to constrain the risk of housing price changes to banks. There is some evidence that real estate stimulating policies, particularly tax-related stimulating policies, increase the risk of housing price changes to banks.

Unlike the first and the fourth essays, the second and the third essays analyze the connectedness of equity volatilities. The results of the second essay suggest that even though public attention in China has been mainly fixed on the risks of real estate firms and real estate market in recent years, policy makers should also consider the potential risks of banks, particularly the medium-sized banks. The results of the second essay also indicate that for maintaining financial stability, policy makers should pay close attention to the spillover effect of the largest real estate firms and the medium-sized banks, because they have the highest average rankings of systemic importance and take less time to transit to the highest systemic importance rankings. The overall findings of the third essay, on the other hand, indicate that market participants perceive banking, real estate, construction and materials, industrial transportation, and chemicals as crucial industries in China from the perspective of volatility connectedness or risk spillovers. Hence, in addition to the macroeconomic announcements related to Chinese manufacturing and industrial output that may affect the global financial markets (Baum, Kurov & Wolfe 2015), economic news about these crucial industries in China is also likely to influence the global financial stability and economic prospects. In sum, the results of the thesis provide new insights into some aspects of financial contagion, risk measurement, monitoring, and regulation. Moreover, the results of the thesis can also be used as input for portfolio construction and management.

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Full length article

Discount rate or cash flow contagion? Evidence from the recent financial crises☆

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ABSTRACT

Breaking the US and Greek equity market returns into a discount rate component and a cash flow component by the method of Campbell (1991), the study investigates the discount rate and cash flow contagion of the subprime mortgage crisis and European sovereign debt crisis to the Nordic equity markets. The study shows that the subprime crisis displays both discount rate contagion and cash flow contagion to the Nordic markets and the effect of discount rate contagion is more pronounced. The sovereign debt crisis, on the other hand, does not show either discount rate contagion or cash flow contagion to the Nordic markets. However, the study provides some evidence that expectations of lower future cash flows resulting from the sovereign debt crisis spread to the Finnish market.

1. Introduction

Previous studies on equity market contagion concentrate on the overall contagion effect of shocks to the equity returns in the crisis-originating country on the equity returns in other countries (e.g., Forbes and Rigobon, 2002; Bekaert et al., 2005; Baur, 2012; Bekaert et al., 2014). The study by Campbell (1991) suggests that shocks to equity returns can be decomposed into two components: a discount rate news component and a cash flow news component, reflecting changes in expectation of future discount rates and changes in expectation of future dividends, respectively. Hence, an interesting question is whether the overall contagion effect is from the discount rate (news) component or the cash flow (news) component of equity returns. The answer to this question may have important policy implications. The decrease of the equity market returns in the crisis-originating country could result from expectations of higher future discount rates (cost of capital), or from expectations of lower future corporate earnings, or from both. Consequently, contagion from the discount rate component would suggest that expectations of higher future discount rates transmit from the crisis-originating country to other countries and thus economic policies aiming at lowering future discount rates or cost of capital may be more effective. In contrast, contagion from the cash flow component would imply that expectations of lower future corporate earnings spread from the crisis-originating country to other countries and thus economic policies aiming at directly increasing corporate earnings may be more effective.

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The purpose of the study is to investigate the discount rate and cash flow contagion of the US subprime mortgage crisis and European sovereign debt crisis to the Nordic equity markets.[1] Specifically, treating US and Greece as the two countries where the subprime crisis and European debt crisis originated, the study examines the discount rate contagion and cash flow contagion of these two countries to each of the four Nordic countries (Denmark, Finland, Norway and Sweden). Given that the four Nordic countries are geographically close and economically homogenous and each of them has its own currency, Nordic equity markets to some extent provide a "controlled experiment" for studying the impact of currency difference on the contagion effect.

The study is closely related to the previous research of Ammer and Mei (1996), Phylaktis and Ravazzolo (2002), Engsted and Tanggaard (2004), Baele and Soriano (2010), and Wang et al. (2013). Decomposing stock returns by the method of Campbell (1991), Ammer and Mei (1996) investigate the financial and economic linkages of 15 international stock markets. They measure financial linkages by the correlations between discount rate news components and economic linkages by the correlations between cash flow news components. In the same spirit, Phylaktis and Ravazzolo (2002) examine the financial and economic integration of the stock markets in the US and Pacific-Basin countries, Engsted and Tanggaard (2004) document the comovements of the stock markets in the US and UK, and Wang et al. (2013) study the discount rate components correlation and cash flow components correlation between mainland China and Hong Kong stock markets. Baele and Soriano (2010) explore the financial and economic integration of European stock markets with the US market, defining the beta of a local market with the US discount rate component as a measure of financial integration and the beta of a local market with the US cash flow component as a measure of economic integration.

However, the study differs from the previous studies in the following ways. Firstly, to our best knowledge, the study is the first to investigate the contagion effect of both the discount rate component and cash flow component of equity returns, focusing on the recent financial crises.[2] More specifically, we first decompose the equity returns of the US and Greek market into a discount rate component and a cash flow component by the vector autoregressive (VAR) framework of Campbell (1991). Then we study the contagion of the discount rate component and cash flow component separately. Secondly, while previous studies use correlation coefficients to examine the linkages of international equity markets (e.g., Ammer and Mei, 1996; Phylaktis and Ravazzolo, 2002; Engsted and Tanggaard, 2004), this study uses the spillover indexes of Diebold and Yilmaz (2012) to analyze the contagion effect of the recent financial crises. As pointed out by Forbes and Rigobon (2002), estimates of correlation coefficients during crisis periods may be biased upward due to the impact of high market volatility. On the other hand, the spillover indexes of Diebold and Yilmaz (2012) are straightforward to compute and can be used to study both the total spillovers and the directional spillovers between different financial markets (see e.g., Diebold and Yilmaz, 2012; Zhou et al., 2012; Antonakakis and Vergos, 2013). Thirdly, the study compares the contagion effect of two financial crises. This comparison could deepen our understanding of the different characteristics of the two financial crises.

The study reveals that the subprime crisis displays both discount rate contagion and cash flow contagion to the Nordic markets, with the effect of discount rate contagion being more pronounced, while the sovereign debt crisis does not show either discount rate contagion or cash flow contagion to the Nordic markets. The study also provides some evidence that the cash flow component of the Greek market has significantly larger impact on the Finnish market during the current sovereign debt crisis, implying that expectations of lower future cash flows resulting from the sovereign debt crisis spread to the Finnish market and thus economic policies aiming at directly increasing Finnish corporate earnings may be more effective.

The remainder of the study proceeds as follows. Section 2 reviews the related literature. Section 3 describes the data used in the study. Section 4 presents the methods. Section 5 shows the empirical results and Section 6 concludes the study.

2. Related literature

One line of related literature is the studies on return decompositions. Utilizing the log-linear return approximation in Campbell and Shiller (1988), Campbell (1991) shows that unexpected stock returns can be decomposed into two components (news about future returns and news about future dividends) and proposes a VAR method to obtain each of those two components. Campbell and Vuolteenaho (2004) use the VAR based return decomposition approach to break the beta of a stock into a cash-flow beta and a discount-rate beta. They show that the two-beta model can explain the size and value anomalies in stock returns.

The seminal work of Campbell (1991) and Campbell and Vuolteenaho (2004) has generated numerous applications of the VAR based return decomposition approach (e.g., Ammer and Mei, 1996; Baele and Soriano, 2010; Cenedese and Mallucci, 2016; Engsted and Tanggaard, 2004; Khan, 2008; Phylaktis and Ravazzolo, 2002; Wang et al., 2013). However, Chen and

[1] In this study, contagion refers to the intensified spillover effects during crisis period relative to tranquil period. Previous literature proposes alternative definitions of contagion (see e.g., Bekaert et al., 2005 and Forbes, 2012). Previous studies define linkages of discount rate components as financial linkages and linkages of cash flow components as economic linkages (e.g., Ammer and Mei, 1996; Baele and Soriano, 2010). Thus contagion from the discount rate component may be referred to as financial contagion and contagion from the cash flow component as economic contagion.

[2] Phylaktis and Ravazzolo (2002) study the financial and economic integration of the stock markets in the US and Pacific-Basin countries. In the section of robustness check for the influence of the Asian financial crisis on their findings, they compare the discount rate component correlations and cash flow component correlations during the pre-crisis period and the post-crisis period. However, they focus on the Asian financial crisis and do not specifically study the correlations of the return components during the post-crisis period since their "post-crisis period" (1990.01-1998.12) also includes the time up to the crisis.

Zhao (2009) point out that the VAR based return decomposition approach has some limitations: this approach directly estimates the discount rate news and computes the cash flow news as the residual; since the discount rate news is not accurately estimated due to the low predictive power for asset returns, the resulting cash flow news incorporates the large misspecification error of the discount rate news; furthermore, the return decompositions could be sensitive to the choice of state variables. To address these limitations, Chen and Zhao propose some solutions, such as estimating directly both the discount rate news and the cash flow news. Engsted et al. (2012) further discuss the limitations of VAR based return decomposition approach. They emphasize the importance of including asset price (or dividend-yield in equity return decomposition) as one of the state variables in the VAR model. They stress that for equity return decomposition, when dividend-yield is included as one of the state variables in the first-order VAR model and the information set is identical for the computation of cash flow news or discount rate news, the return decomposition will be unaffected whether one of the news component is directly estimated or both news component are directly estimated; in addition, the sensitivity problem suggested by Chen and Zhao (2009) may be less significant if dividend-yield is included as one of the state variables.

Another line of related literature investigates the spillover or contagion effect in the financial markets. For instance, Forbes and Rigobon (2002) develop a correlation measure that corrects for the effect of market volatility on the test for contagion. Using this adjusted correlation coefficient, they show that no contagion exists during the 1987 US stock market crash, 1994 Mexican devaluation and 1997 Asian crisis. Bekaert et al. (2014) use a three-factor model to study the equity market contagion of the 2007–2009 subprime crisis. They find that the contagion effect from the US markets to the global equity markets is statistically significant but economically small. Baur (2012) finds evidence of domestic and international contagion between financial sector stocks and non-financial sector stocks during the global financial crisis of 2007–2009. Based on the joint probability of default, the study by Gorea and Radev (2014) shows that shocks to the troubled euro area countries (Greece, Ireland, Italy, Portugal and Spain) are transmitted to the rest of euro area countries mainly through real economy linkages (proxied by bilateral trade flows).

Diebold and Yilmaz (2012) introduce measures of spillovers that are based on the generalized forecast-error variance decompositions. They use these measures of spillovers to investigate the volatility transmission across four US asset classes: stocks, bonds, foreign exchange and commodities. They find that volatility spillovers among the four asset classes were stronger during the subprime crisis, especially the spillovers from the stock market to other markets. Alter and Beyer (2014) analyze the spillovers between sovereign and bank CDS spreads during the European sovereign debt crisis. They show that spillover effects between banks and sovereigns were stronger prior to key financial market events and policy interventions. Sugimoto et al. (2014) assess the spillover effects of international stock markets, commodities and foreign exchange rates on seven African stock markets. They conclude that global stock markets are the main source of spillovers to the African markets and the African markets were mainly affected by the European sovereign debt crisis rather than the US subprime crisis.

3. Data

Monthly stock market data for the four Nordic countries (MSCI index), Greece (FTSE index), Germany (DAX30) and US (S&P500) were retrieved from Thomson Reuters Datastream. Dividend yield for the FTSE Greece index and S&P500 index was also obtained from Datastream. The selected indexes are the total return index in local currency.[3] In order to construct the value spread for the Greek market, we downloaded from Datastream the total return indexes of MSCI Greece small growth stocks and MSCI Greece small value stocks. The data for constructing the value spread of the US market were obtained from Professor Kenneth French's data library. Greece 3-month Treasury bill rate is from Datastream and Greece 10-year government bond rate is from Federal Reserve Bank of St. Louis. US 3-month Treasury constant maturity rate and the spread between 10-Year Treasury constant maturity rate and 3-Month Treasury constant maturity rate are also from Federal Reserve Bank of St. Louis.

For the purpose of return decomposition, we choose a relatively longer sample period for Greece (from June 1998 to December 2012) and US (from February 1988 to December 2012).[4] For the German and Nordic markets, the data are from January 2004 to December 2012. We define January 2004 to June 2007 as the pre-crisis period, July 2007 to December 2009 as the subprime crisis period, and January 2010 to December 2012 as the sovereign debt crisis period. To avoid the impact of the burst of dot-com bubble, we define January 2004 to June 2007 as the pre-crisis period for both the subprime crisis and the sovereign debt crisis. Following previous studies that define the summer of 2007 as the beginning point of the subprime crisis (Bekaert et al., 2014; Fahlenbrach and Stulz, 2011), we treat July 2007 as the starting point of the US subprime crisis. In addition, since NBER considers June 2009 as the trough of the recent economic cycle and the European debt crisis initiated from Greece at the end of 2009, we define December 2009 as the end point of subprime crisis and the starting point of sovereign debt crisis. Greek 10-year government bond yield reached the highest level of 29.24% in February 2012 and then

[3] Mink (2015) provides arguments for using local currency in the analysis of equity market contagion.

[4] The beginning point of the sample period for Greece and US is determined by the data availability in Datastream. Sample period in this study refers to sample period for returns (sample period for price indexes is one month earlier). Following previous studies that use long sample period for return decomposition (e.g., Baele and Soriano, 2010; Campbell and Vuolteenaho, 2004), we choose a relatively longer sample period for Greece and US for return decomposition.

gradually decreased to 13.33% in December 2012, which suggests that the ongoing sovereign debt crisis reached its peak level in 2012. Hence, to capture the peak impact of the Greek market on the Nordic markets, we only include data until December 2012 for the sovereign debt crisis.

4. Empirical method

The method of the study involves two steps. In the first step, we decompose the US stock market return and the Greek stock market return into a cash flow component and a discount rate component (Campbell, 1991; Campbell and Vuolteenaho, 2004). In the second step, we employ a vector auto-regression model to obtain the forecast-error variance decomposition of returns and construct the spillover indexes (Diebold and Yilmaz, 2012).

4.1. Return decomposition

Building on the log-linear return approximation of Campbell and Shiller (1988), Campbell (1991) presents the following decomposition of unexpected excess returns.[5]

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \equiv N_{CF,t+1} - N_{DR,t+1}, \quad (1)$$

where r_{t+1} is the log excess return from time t to time t + 1, E_t is the expectation conditional on the information at time t, d_{t+1} is the log dividend, Δ denotes the one period difference, $N_{CF,t+1}$ denotes the cash flow component of the unexpected return and $N_{DR,t+1}$ denotes the discount rate component of the unexpected return.

Let z_{t+1} be a k-by-1 vector whose first element is r_{t+1} and assume z_{t+1} follows the following VAR(1) model:

$$z_{t+1} = c + Az_t + u_{t+1}, \quad (2)$$

where c is a k-by-1 vector of parameters, A is a k-by-k matrix of parameters and u_{t+1} is a k-by-1 vector of errors. Eq. (2) can be used to show that

$$N_{DR,t+1} \equiv (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} = e1'\rho A(I - \rho A)^{-1}u_{t+1}, \quad (3)$$

where $e1$ is a k-by-1 vector, whose first element is one and zeros elsewhere; ρ is a constant smaller than one; I is a k-by-k identity matrix. Eq. (2) also suggests that $r_{t+1} - E_t r_{t+1}$ is equal to the first element of u_{t+1}. Therefore, we can back out the cash flow component from Eq. (1):

$$N_{CF,t+1} = r_{t+1} - E_t r_{t+1} + N_{DR,t+1} = e1'u_{t+1} + e1'\rho A(I - \rho A)^{-1}u_{t+1} = [e1' + e1'\rho A(I - \rho A)^{-1}]u_{t+1}. \quad (4)$$

Following Campbell and Vuolteenaho (2004) and Engsted et al. (2012), we include the following four variables in the state vector z_{t+1}: log excess return (monthly log return in excess of the 3-month government bond rate), log dividend yield, term spread (the difference between 10-year government bond yield and 3-month government bond yield, in annualized fraction number), and small-stock value spread. Small-stock value spread for the US market is the difference between the log BE/ME of the small high book-to-market portfolio and small low book-to-market portfolio (see the Appendix to Campbell and Vuolteenaho, 2004).[6] Due to the data availability, we construct the small-stock value spread for the Greek market as the difference between the cumulative returns of the small growth stocks and small value stocks in the previous year (proxied by the difference between MSCI small growth stock returns and MSCI small value stock returns in the previous year). Eleswarapu and Reinganum (2004) provide evidence that return differences between growth stocks and value stocks in the prior 36 months can predict stock market returns. To construct a comparable measure of value spread to the US market, we use cumulative returns in the previous year, instead of the prior 36 months.

We compute the return decompositions separately for the subprime crisis and sovereign debt crisis. To avoid the impact of the financial crises on the estimation of parameters c and A in Eq. (2), we estimate Eq. (2) using data before the financial crises.[7] In particular, for the subprime crisis we include the US data over the period February 1988–June 2007 to estimate Eq. (2); for the sovereign debt crisis, we use the Greek data over the period June 1998–June 2007 to estimate Eq. (2). Then we obtain the return decompositions during the pre-crisis period by Eqs. (3) and (4).

To compute the return decompositions during the crisis period, we first demean the data by the sample average during the crisis period (the data for the last month before the crisis are also included in order to obtain the return decomposition

[5] In a more strict sense, the relationship in Eq. (1) holds only for unexpected real returns. When real interest rates are constant, Eq. (1) also holds for unexpected excess returns (see the Appendix to Campbell and Vuolteenaho, 2004). As in Campbell and Vuolteenaho (2004), we use excess returns instead of real returns.

[6] Since the data obtained from the data library of professor Kenneth French only have yearly value for BE/ME, we use the average BE/ME of year t-1 and year t to represent the value of BE/ME in June of year t. This approximation could be accurate since the BE/ME values are stable over the years.

[7] We assume that the financial crises have only changed the mean value of z_t and did not change the parameter A in Eq. (2).

Table 1
VAR parameter estimates for the US market.

	Constant	$R^e_{US,t}$	dp_t	TS_t	VS_t	R^2
$R^e_{US,t+1}$	0.0589	−0.0623	0.0130	−0.1741	0.0116	0.0190
	(2.0201)	(−0.9385)	(1.7823)	(−0.7937)	(0.4823)	
dp_{t+1}	−0.0443	−0.0937	0.9900	0.1991	−0.0238	0.9898
	(−1.6136)	(−1.4996)	(144.4200)	(0.9634)	(−1.0500)	
TS_{t+1}	−0.0005	0.0002	−0.0002	0.9817	−0.0021	0.9649
	(−0.2987)	(0.0572)	(−0.3977)	(75.9407)	(−1.4970)	
VS_{t+1}	0.0296	0.0303	0.0082	−0.0871	0.8328	0.7023
	(0.6625)	(0.2986)	(0.7398)	(−0.2592)	(22.5710)	

Notes: the table reports the parameter estimates of the VAR (1) model in Eq. (2) for the US market.$R^e_{US,t+1}$ is the log excess return of the US market at month t + 1, dp_{t+1} is the log dividend-yield at month t + 1, TS_{t+1} is the term-spread at month t + 1, and VS_{t+1} is the small stock value spread for the US market at month t + 1. The first row, third row, fifth row, and seventh row show the parameter estimates for the equation of log excess return, log dividend-yield, term-spread, and small stock value spread, respectively. T-statistics are shown in the parentheses. The VAR model is estimated using data from February 1988 to June 2007.

for the first month of the crisis period). Given the estimated value of A before the crisis, we calculate the residual using the demeaned value of z_t (i.e., $u_{t+1} = z_{t+1} - Az_t$).Finally, by Eqs. (3) and (4) we obtain the return decompositions during the crisis period. In all the return decompositions, we set the constant$\rho \equiv 1/(1+\exp(\bar{x}))$, where $\bar{x}$ is the sample average of log dividend yield during the whole sample period.[8]

4.2. Return spillover indexes

After estimating the cash flow and discount rate components of unexpected returns, we derive the return spillover indexes from the generalized forecast-error variance decomposition of each of the four Nordic equity markets (see Koop et al., 1996; Pesaran and Shin, 1998; Diebold and Yilmaz, 2012). We compute both the directional and total spillover indexes (Diebold and Yilmaz 2012). Total spillover index measures the contribution of cross-market spillovers to the total forecast-error variance; directional spillover index measures the directional spillovers between a given market and all the other markets.

We estimate the forecast-error variance decomposition and the spillover indexes separately for the pre-crisis period and crisis period, controlling for the impact of the regional equity market and global equity market which are represented by the German equity market and US equity market, respectively. In other words, when investigating the spillover effect from the US market to the Nordic markets, we also include the German market; when investigating the spillover effect from the Greek market to the Nordic markets, we also include the German market and US market.

It should be noted that in the study we use a fixed-window rather than a rolling-window to calculate the spillover indexes. We believe that the fixed-window method may be more appropriate for investigating the contagion effect of financial crises. To compute the spillover indexes in month t, the rolling-window method uses return data in the previous H (window length) months. In consequence, the spillover indexes for some months during the crisis period are calculated mainly based on the return data from the pre-crisis period. For example, the spillover indexes in the first month of the crisis period are calculated based on the return data over the previous H months which contain H-1 months from the pre-crisis period. In contrast, the fixed-window method computes one set of spillover indexes for the whole crisis period based on the return data during the whole crisis period.

5. Empirical results

This section presents the empirical results: subsection 5.1 presents the empirical results of return decompositions and subsection 5.2 presents the empirical results of return spillovers.

5.1. Empirical results of return decompositions

Tables 1 and 2 report estimates of the parameters in Eq. (2), which are used to compute the two return components. Table 1 shows estimates of the parameters in Eq. (2) for the US market, using data from February 1988 to June 2007. Four state variables are included in the VAR model in Eq. (2): log excess return of the aggregate market, log dividend-yield, term-spread, and small stock value spread. The estimates for the excess return equation suggest that dividend-yield has predictive power for the aggregate market return: higher past dividend-yield implies higher future return. The positive

[8] The formula for ρ in the original log-linear return approximation of Campbell and Shiller (1988) is $\rho \cong P_t/(P_t + D_{t-1})$, where P_t is the price of the stock at the beginning of period t and D_{t-1} is the dividend paid out by the stock during period t-1. Or equivalently, $\rho \cong 1/\left(1 + D_{t-1}/P_t\right) = 1/\left(1 + \exp(ln(D_{t-1}/P_t)\right))$.

Table 2
VAR parameter estimates for the Greek market.

	Constant	$R^e_{Greece,t}$	dp_t	TS_t	VS_t	R^2
$R^e_{Greece,t+1}$	0.3577	0.0065	0.0960	−1.8984	−0.1918	0.0530
	(2.0067)	(0.0655)	(2.0034)	(−2.1409)	(−2.1315)	
dp_{t+1}	−0.7255	−0.0120	0.8037	3.0641	0.1316	0.9263
	(−3.1194)	(−0.0920)	(12.8498)	(2.6488)	(1.1211)	
TS_{t+1}	0.0046	−0.0017	0.0011	0.9411	−0.0065	0.9655
	(0.4918)	(−0.3242)	(0.4543)	(20.3486)	(−1.3822)	
VS_{t+1}	0.1657	−0.1351	0.0466	−0.9108	0.8004	0.8368
	(1.6633)	(−2.4250)	(1.7377)	(−1.8378)	(15.9157)	

Notes: the table reports the parameter estimates of the VAR (1) model in Eq. (2) for the Greek market. $R^e_{Greece,t+1}$ is the log excess return of the Greek market at month t + 1, dp_{t+1} is the corresponding log dividend-yield at month t + 1, TS_{t+1} is the Greek term-spread at month t + 1, and VS_{t+1} is the small stock value spread for the Greek market at month t + 1. The first row, third row, fifth row, and seventh row show the parameter estimates for the equation of log excess return, log dividend-yield, term-spread, and small stock value spread, respectively. T-statistics are shown in the parentheses. The VAR model is estimated using data from June 1998 to June 2007.

Table 3
Descriptive statistics of the return decompositions.

	US return decompositions				Greek return decompositions			
	Pre-crisis period		Crisis period		Pre-crisis period		Crisis period	
	N_DR	N_CF	N_DR	N_CF	N_DR	N_CF	N_DR	N_CF
Mean	0.0031	0.0051	−0.0015	−0.0014	−0.0048	0.0151	−0.0051	−0.0039
Median	0.0015	0.0066	−0.0011	0.0067	−0.0045	0.0205	−0.0100	−0.0357
Maximum	0.0287	0.0273	0.0819	0.0641	0.0656	0.1128	0.6369	0.8596
Minimum	−0.0192	−0.0244	−0.0741	−0.0974	−0.0736	−0.0909	−0.5024	−0.5465
Std. Dev.	0.0103	0.0131	0.0293	0.0428	0.0315	0.0497	0.1980	0.2514
Obs.	42	42	30	30	42	42	36	36

Notes: the table reports the descriptive statistics of the return decompositions during the pre-crisis period and the crisis period. N_DR is the discount rate component of the unexpected returns and N_CF is the cash flow component of the unexpected returns. For both the US return decompositions and the Greek return decompositions, the pre-crisis period is from January 2004 to June 2007. The crisis period for the US return decompositions is from July 2007 to December 2009 and the crisis period for the Greek return decompositions is from January 2010 to December 2012.

predictive power of dividend-yield is consistent with Engsted et al. (2012). The proportion of return variance explained by the four state variables is 1.9%, which is close to the corresponding number of 2.57% in Campbell and Vuolteenaho (2004). In contrast with Campbell and Vuolteenaho (2004), the coefficient estimates for the other three explanatory variables in the return equation are not statistically significant, which may be due to the shorter sample period used for parameter estimation in this study. The other three state variables (log dividend-yield, term-spread and small stock value spread) appear to follow AR(1) process. With characteristic root close to one, log dividend-yield and term-spread are highly persistent.

Table 2 reports the parameter estimates of the VAR(1) model in Eq. (2) for the Greek market, using data from June 1998 to June 2007. Similar to the case of parameter estimation for the US market, the VAR model includes four state variables constructed for the Greek market: log excess return, log dividend-yield, term-spread and small stock value spread. The first row of Table 2 shows that log dividend-yield positively predicts Greek market return while term-spread and small stock value spread negatively predict Greek market return. The finding that small stock value spread negatively predicts (Greek) aggregate market return is in line with Campbell and Vuolteenaho (2004) and supports our proxy for this variable. However, the negative predictive ability of term-spread for the Greek market contrasts with the positive predictive ability of term-spread for the US market in Campbell and Vuolteenaho (2004). R^2 of the excess return equation is higher than the corresponding R^2 for the US market, indicating that the four state variables have higher predictive power for the Greek market returns. The coefficient estimates for the equation of log dividend-yield show that future dividend-yield is positively related to past dividend-yield and term-spread. The estimates for the equation of term-spread indicate that term-spread follows highly persistent AR(1) process. Parameter estimates in the last two rows of Table 2 show that all the four state variables have some predictive power for the small stock value spread.

Table 3 presents the descriptive statistics of the return decompositions based on the estimates of parameters in Tables 1 and 2. The value of ρ for the US return decompositions is set to 0.98, which is computed from the sample average of the US log dividend yield over the whole sample period (February 1988 to December 2009). In a similar way, the value of ρ for the Greek return decompositions is set to 0.97, which is computed from the sample average of the Greek log dividend yield over the whole sample period (June 1998 to December 2012).[9]

[9] The main findings of the study remain unchanged when the value of ρ is set to 0.951/12 for both the US return decompositions and the Greek return decompositions (results available upon request).

Table 4
Percentage of forecast-error variance explained by the US discount rate component.

	Pre-crisis period	Crisis period	% Change
X = Denmark	12.85	31.51	145.17
X = Finland	6.30	24.86	294.59
X = Norway	9.95	26.67	168.06
X = Sweden	17.48	30.13	72.38

Notes: the table reports the percentage of 6-month-ahead forecast error variance explained by the discount rate component of US returns. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{DR,US}, R_{Ger}, X]'$, where $N_{DR,US}$ is the discount rate component of the US returns, R_{Ger} is the return of the German market, and X is the return of one of the Nordic markets. Pre-crisis period is from January 2004 to June 2007 and crisis period is from July 2007 to December 2009.

For the US return decompositions, the average discount rate component and cash flow component during the pre-crisis period are 0.31% and 0.51%, respectively. For the Greek return decompositions, the average values of the discount rate component and cash flow component during the pre-crisis period are −0.48% and 1.51%, respectively. For both the US return decompositions and the Greek return decompositions, the average value of the discount rate component or cash flow component is lower during the crisis period than the pre-crisis period. For both the discount rate component and the cash flow component, the standard deviation during the crisis period is larger than the corresponding standard deviation during the pre-crisis period. Moreover, standard deviation of the cash flow component is larger than that of the discount rate component at the same period. The finding of larger standard deviation for the cash flow component is in line with Cenedese and Mallucci (2016), but differs from Campbell (1991) and Campbell and Vuolteenaho (2004), which may be because of our use of different sample period, predictive variables and the value of ρ.

5.2. Empirical results of return spillovers

To examine the contagion effects of the two financial crises, we compare the spillover effects during the pre-crisis period with the spillover effects during the crisis-period. In particular, for the subprime crisis we estimate a VAR model during the pre-crisis period and a VAR model during the crisis period. For the discount rate spillovers, the vector of variables in the VAR model is $\left[N_{DR,US}, R_{Ger}, X\right]'$, where $N_{DR,US}$ is the discount rate component of the US returns, R_{Ger} is the return of the German market, and X is the return of one of the Nordic markets; for the cash flow spillovers, the vector of variables in the VAR model is $\left[N_{CF,US}, R_{Ger}, X\right]'$, where $N_{CF,US}$ is the cash flow component of the US returns. In a similar way, for the sovereign debt crisis we estimate a VAR model during the pre-crisis period and a VAR model during the crisis period, with the vector of variables being $\left[N_{DR,Greece}, R_{Ger}, R_{US}, X\right]'$ or $\left[N_{CF,Greece}, R_{Ger}, R_{US}, X\right]'$. For all the VAR models, we use a VAR model of order 1 (in almost all the cases, residuals from a VAR(1) model pass the test for white noise at the 5% significance level). After estimating each VAR model, we derive the (normalized) generalized variance decompositions and compute the spillover indexes. In this section, we report the results of variance decompositions and spillover indexes based on a forecast horizon of 6 month.[10]

Tables 4 and 5 present the results of spillovers from the discount rate component of US returns. Table 4 shows that compared to the pre-crisis period, the discount rate component of US returns accounts for larger proportion of the forecast error variance of the Nordic markets during the crisis period. For instance, before the financial crisis only 6.3% of the forecast error variance of the Finnish market is due to the discount rate component of US returns; in contrast, the proportion of forecast error variance due to the discount rate component of US returns increases by 294.6% to 24.9% during the crisis period.

Table 5 reports the total spillovers, the spillovers from other markets to the discount rate component of US returns, and the spillovers from the discount rate component of US returns to the other markets.[11] Comparing panel A and panel B, we observe that there is significant increase in the three spillover indexes during the crisis period. For example, when Denmark is included as the third variable in the VAR model, the total spillover index increases from 43.2% to 57.4%, the spillover from German market and Danish market to the discount rate component increases from 42.8% to 55.4%, and the spillover from the discount rate component to German market and Danish market increases from 37.0% to 66.5%. On average, the total spillover rises by 38.4% (from 40.98% to 56.70%), the spillover from other markets to the discount rate component rises by 35.1% (from 41.14% to 55.57%), and the spillover from the discount rate component to other markets rises by 66.7% (from 37.31% to 62.21%). Moreover, the net spillovers from the discount rate component to other markets, which is the difference between column three and column two of Table 5, also intensify during the crisis: on average, the net spillovers increase from −3.8% (37.31%–41.14%) to 6.6% (62.21%–55.57%).

[10] For all the VAR models, the forecast-error variance decompositions are quantitatively similar from month 2 to month 10. Hence, the variance decompositions and spillover indexes should be similar if a forecast horizon other than 6 month is used.
[11] For the subprime crisis, "other markets" refers to German market and one of the Nordic markets.

Table 5
Spillovers of the discount rate component of US returns.

	From others to N_DR	From N_DR to others	Total spillovers
Panel A: Pre-crisis period			
X = Denmark	42.79	36.98	43.18
X = Finland	37.05	35.21	33.61
X = Norway	39.72	36.08	38.47
X = Sweden	44.99	40.95	48.67
Average	41.14	37.31	40.98
Panel B: Crisis period			
X = Denmark	55.38	66.46	57.40
X = Finland	53.08	57.57	56.00
X = Norway	55.83	61.33	56.49
X = Sweden	57.99	63.47	56.92
Average	55.57	62.21	56.70

Notes: the table reports the total spillovers, the spillovers from other markets to the discount rate component of US returns ("From others to N_DR"), and the spillovers from the discount rate component of US returns to the other markets ("From N_DR to others"). Here, "other markets" refers to German market and one of the Nordic markets. Spillover indexes are computed based on a forecast horizon of 6 month. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{DR,US}, R_{Ger}, X]'$, where $N_{DR,US}$ is the discount rate component of the US returns, R_{Ger} is the return of the German market, and X is the return of one of the Nordic markets. The last row of each panel is the average of the previous four rows (or the average spillovers across the four Nordic markets). Pre-crisis period is from January 2004 to June 2007 and crisis period is from July 2007 to December 2009.

Table 6
Percentage of forecast-error variance explained by the US cash flow component.

	Pre-crisis period	Crisis period	% Change
X = Denmark	14.88	23.57	58.42
X = Finland	18.92	25.01	32.15
X = Norway	21.39	23.57	10.20
X = Sweden	15.92	22.54	41.61

Notes: the table reports the percentage of 6-month-ahead forecast error variance explained by the cash flow component of US returns. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{CF,US}, R_{Ger}, X]'$, where $N_{CF,US}$ is the cash flow component of the US returns, R_{Ger} is the return of the German market, and X is the return of one of the Nordic markets. Pre-crisis period is from January 2004 to June 2007 and crisis period is from July 2007 to December 2009.

Table 7
Spillovers of the cash flow component of US returns.

	From others to N_CF	From N_CF to others	Total spillovers
Panel A: Pre-crisis period			
X = Denmark	37.23	34.06	40.62
X = Finland	37.81	40.09	35.06
X = Norway	41.05	42.32	40.45
X = Sweden	40.66	33.76	45.84
Average	39.19	37.56	40.49
Panel B: Crisis period			
X = Denmark	58.13	57.11	57.01
X = Finland	60.78	55.69	58.67
X = Norway	57.87	56.20	56.25
X = Sweden	60.66	53.64	57.15
Average	59.36	55.66	57.27

Notes: the table reports the total spillovers, the spillovers from other markets to the cash flow component of US returns ("From others to N_CF"), and the spillovers from the cash flow component of US returns to the other markets ("From N_CF to others"). Here, "other markets" refers to German market and one of the Nordic markets. Spillover indexes are computed based on a forecast horizon of 6 month. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{CF,US}, R_{Ger}, X]'$, where $N_{CF,US}$ is the cash flow component of the US returns, R_{Ger} is the return of the German market, and X is the return of one of the Nordic markets. The last row of each panel is the average of the previous four rows (or the average spillovers across the four Nordic markets). Pre-crisis period is from January 2004 to June 2007 and crisis period is from July 2007 to December 2009.

The overall results in Tables 4 and 5 indicate that the spillover effects from the discount rate component of US returns to the Nordic markets become much stronger during the crisis period relative to the pre-crisis period, providing evidence that there is discount rate contagion during the subprime crisis.

Tables 6 and 7 show the results of spillovers from the cash flow component of US returns. As in the case of discount rate component, the cash flow component has larger effect during the crisis period than the pre-crisis period. The proportion of forecast-error variance explained by the US cash flow component increases by 58.4%, 32.2%, 10.2%, and 41.6% for the Danish,

Table 8
Percentage of forecast-error variance explained by Greece discount rate component.

	Pre-crisis period	Crisis period	% Change
X = Denmark	4.63	1.55	−66.45
X = Finland	10.76	2.45	−77.23
X = Norway	5.41	2.03	−62.47
X = Sweden	7.11	1.23	−82.76

Notes: the table reports the percentage of 6-month-ahead forecast error variance explained by the discount rate component of the Greek market returns. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{DR,Greece}, R_{Ger}, R_{US}, X]'$, where $N_{DR,Greece}$ is the discount rate component of the Greek market returns, R_{Ger} is the return of the German market, R_{US} is the return of the US market, and X is the return of one of the Nordic markets. Pre-crisis period is from January 2004 to June 2007 and crisis period is from January 2010 to December 2012.

Table 9
Spillovers of the discount rate component of Greek returns.

	From others to N_DR	From N_DR to others	Total spillovers
Panel A: Pre-crisis period			
X = Denmark	20.02	11.52	42.37
X = Finland	29.68	24.04	43.11
X = Norway	24.63	12.17	41.48
X = Sweden	26.44	16.96	48.35
Average	25.19	16.17	43.83
Panel B: Crisis period			
X = Denmark	20.42	3.91	44.56
X = Finland	20.34	5.98	44.40
X = Norway	13.59	4.25	44.56
X = Sweden	18.57	3.70	47.22
Average	18.23	4.46	45.19

Notes: the table reports the total spillovers, the spillovers from other markets to the discount rate component of Greek market returns ("From others to N_DR"), and the spillovers from the discount rate component of Greek market returns to the other markets ("From N_DR to others"). Here, "other markets" refers to German market, US market, and one of the Nordic markets. Spillover indexes are computed based on a forecast horizon of 6 month. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{DR,Greece}, R_{Ger}, R_{US}, X]'$, where $N_{DR,Greece}$ is the discount rate component of the Greek market returns, R_{Ger} is the return of the German market, R_{US} is the return of the US market, and X is the return of one of the Nordic markets. The last row of each panel is the average of the previous four rows (or the average spillovers across the four Nordic markets). Pre-crisis period is from January 2004 to June 2007 and crisis period is from January 2010 to December 2012.

Finnish, Norwegian and Swedish market, respectively. However, the increase of the US cash flow effect seems to be smaller than that of the US discount rate effect (see the last column of Table 4).

The results in Table 7 indicate that spillovers from the cash flow component of US returns are stronger during the crisis period than the pre-crisis period. Both the directional spillovers and the total spillovers have intensified during the subprime crisis. On average, cash flow spillovers to other markets increase by 48.2% (from 37.56% to 55.66%), spillovers from other markets to the cash flow component increases by 51.5% (from 39.19% to 59.36%), and total spillovers increases by 41.4% (from 40.49% to 57.27%). Therefore, based on our definition of contagion, the results in Tables 6 and 7 suggest that there is cash flow contagion during the subprime crisis. This cash flow contagion effect, however, only occurs for the total spillovers and the two directional spillovers (from the cash flow component to other markets and from other markets to the cash flow component). The net spillovers from the cash flow component to other markets (i.e., the difference between column three and column two of Table 7) appear to be weaker during the crisis period: on average, the net spillovers decrease from −1.6% (37.56%–39.19%) to −3.7% (55.66%–59.36%).

Comparing the results in Tables 4 and 5 with those in Tables 6 and 7, we can notice three features which reveal that the subprime crisis exhibits stronger discount rate contagion than cash flow contagion. Firstly, the increase of the proportion of forecast-error variance due to the discount rate component is larger than the corresponding increase due to the cash flow component (see the last column of Tables 4 and 6). Secondly, the increase of spillovers from the discount rate component to other markets is larger than the increase of spillovers from the cash flow component to other markets: on average, the spillovers from the discount rate component to other markets increase by 66.7%, whereas the spillovers from the cash flow component to other markets increase by 48.2%. Thirdly, as mentioned above, net discount rate spillovers from the US market to other markets strengthen during the crisis period while net cash flow spillovers from the US market to other markets weaken during the crisis period.

Regarding the spillover effect of the European debt crisis, Tables 8 and 9 present the results of spillovers from the discount rate component of Greek returns. Surprisingly, the fraction of forecast-error variance explained by the discount rate component of Greek returns is smaller during the debt crisis period than the pre-crisis period: the fraction of forecast-error variance attributed to the discount rate component decreases by 66.5%, 77.2%, 62.5%, and 82.8% for Denmark, Finland, Norway, and Sweden, respectively. Although the total spillover indexes in Table 9 show small increases during the crisis

Table 10
Percentage of forecast-error variance explained by Greece cash flow component.

	Pre-crisis period	Crisis period	% Change
X = Denmark	1.63	0.39	−76.37
X = Finland	1.08	4.94	358.80
X = Norway	2.46	1.87	−24.20
X = Sweden	4.61	0.15	−96.82

Notes: the table reports the percentage of 6-month-ahead forecast error variance explained by the cash flow component of the Greek market returns. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{CF,Greece}, R_{Ger}, R_{US}, X]'$, where $N_{CF,Greece}$ is the cash flow component of the Greek market returns, R_{Ger} is the return of the German market, R_{US} is the return of the US market, and X is the return of one of the Nordic markets. Pre-crisis period is from January 2004 to June 2007 and crisis period is from January 2010 to December 2012.

Table 11
Spillovers of the cash flow component of Greek returns.

	From others to N_CF	From N_CF to others	Total spillovers
Panel A: Pre-crisis period			
X = Denmark	26.19	18.40	44.57
X = Finland	31.79	18.27	41.96
X = Norway	31.12	22.42	44.28
X = Sweden	29.00	19.77	48.80
Average	29.53	19.71	44.90
Panel B: Crisis period			
X = Denmark	24.32	8.46	45.88
X = Finland	30.43	10.19	47.41
X = Norway	26.73	11.64	48.68
X = Sweden	23.99	7.46	48.85
Average	26.37	9.43	47.71

Notes: the table reports the total spillovers, the spillovers from other markets to the cash flow component of Greek market returns ("From others to N_CF"), and the spillovers from the cash flow component of Greek market returns to the other markets ("From N_CF to others"). Here, "other markets" refers to German market, US market, and one of the Nordic markets. Spillover indexes are computed based on a forecast horizon of 6 month. For the forecast-error variance decomposition, we estimate a VAR(1) model during the pre-crisis period and a VAR(1) model during the crisis period. The vector of variables in the VAR model is $[N_{CF,Greece}, R_{Ger}, R_{US}, X]'$, where $N_{CF,Greece}$ is the cash flow component of the Greek market returns, R_{Ger} is the return of the German market, R_{US} is the return of the US market, and X is the return of one of the Nordic markets. The last row of each panel is the average of the previous four rows (or the average spillovers across the four Nordic markets). Pre-crisis period is from January 2004 to June 2007 and crisis period is from January 2010 to December 2012.

period, both the spillovers from the discount rate component to other markets and the spillovers from other markets to the discount rate component decline during the crisis period.[12] Thus, the results in Tables 8 and 9 indicate that there is no discount rate contagion during the European debt crisis.

Tables 10, 11 show the cash flow spillover effect of the Greek market. For the three Nordic countries that are not in the Euro area, Table 10 shows that the proportion of forecast-error variance accounted for by the cash flow component decreases during the crisis period. However, for Finland, the only Nordic country in the Euro area, the proportion of forecast-error variance due to the cash flow component increases dramatically during the crisis period, which suggests that the cash flow component of the Greek market exerts significantly larger influence on the Finnish market during the crisis. Similar to the discount rate spillovers in Table 9, Table 11 shows that during the crisis period, directional spillovers between the cash flow component and other markets are weaker and the total spillovers are slightly stronger. The evidence of weaker directional spillovers and stronger total spillovers shown in Tables 9 and 11 suggests that cross-market spillovers between Germany, US and Nordic markets are stronger during the current sovereign debt crisis. Our results (not reported) of forecast-error variance decompositions also support the conclusion that spillovers between Germany, US and Nordic markets become stronger during the ongoing debt crisis, which we interpret as evidence that the occurrence of the sovereign debt crisis caused investors in the Nordic equity markets to be more sensitive to return changes in the German and US equity markets.

In sum, we do not find evidence of discount rate or cash flow contagion for the European debt crisis. In fact, the discount rate and cash flow spillover to the Nordic equity markets seems to be weaker during the crisis. Nevertheless, we find some evidence that the cash flow component of the Greek market has significantly larger impact on the Finnish market during the debt crisis, which implies that to some extent, the influence of the European debt crisis is constrained within the Euro area and this influence is mostly related to the cash flow component (or the economic linkages; see e.g., Ammer and Mei, 1996; Baele and Soriano, 2010). This finding is consistent with that of Gorea and Radev (2014) who suggest that shocks to

[12] For the European debt crisis, "other markets" refers to German market, US market and one of the Nordic markets.

the troubled euro area countries (Greece, Ireland, Italy, Portugal and Spain) are transmitted to the rest of euro area countries mainly through real economy linkages (proxied by bilateral trade flows).

Two issues may be noted. Firstly, previous studies suggest that return decompositions could be sensitive to the predictive variables included in the state vector. To alleviate this problem, we follow the recommendations of Engsted et al. (2012) and include the "theoretically correct" variable, dividend-yield, as one of the predictive variables. Moreover, as a robustness check, we also include two additional predictive variables in the state vector: 3 month T-bill rate and stock variance (see Campbell and Vuolteenaho, 2004; Guo, 2006). Stock variance for a given month is calculated as the sum of squared daily returns on the aggregate US or Greek index over the month. The results from the robustness check (available upon request) provide qualitatively similar findings for the contagion effect of the subprime crisis and debt crisis, except that the forecast error variance of each Nordic market accounted for by the US (Greek) cash flow component is lower during the subprime crisis (sovereign debt crisis).

Secondly, for the sovereign debt crisis, the study finds no discount rate or cash flow contagion over the years 2010–2012. Given that the sovereign debt crisis reached its peak level in 2012 (as suggested by the Greek 10-year government bond yield), including data after 2012 is unlikely to change the main findings about the sovereign debt crisis.

6. Conclusion

The study investigates the contagion effect of the subprime mortgage crisis and European sovereign debt crisis to the Nordic equity markets. Decomposing the aggregate equity market returns of the two crisis-originating countries (US and Greece) into a cash flow component and a discount rate component, the study examines both the discount rate contagion and the cash flow contagion of the two crises. The study shows that the subprime crisis displays both discount rate contagion and cash flow contagion to the Nordic markets, with the effect of discount rate contagion being more pronounced. The sovereign debt crisis, on the other hand, does not show either discount rate contagion or cash flow contagion to the Nordic markets. Nevertheless, for the benchmark case of return decompositions with four state variables, the study shows that the cash flow component of the Greek market has significantly larger impact on the Finnish market during the current sovereign debt crisis, implying that expectations of lower future cash flows resulting from the sovereign debt crisis spread to the Finnish market, the only Nordic market in the Euro area. The overall finding that Nordic markets were mainly affected by the subprime crisis rather than the sovereign debt crisis contrasts with that of Sugimoto et al. (2014) who show that African markets were mainly affected by the European sovereign debt crisis rather than the US subprime crisis.

A potential limitation of the study is that since monthly data are used in the analysis, sample size for the two crisis periods is not large. To address this issue, we only include one Nordic market at a time in the VAR model for forecast-error variance decomposition. Thus, we only take into account the indirect spillovers among the four Nordic markets through German market and US market and ignore the potential direct spillovers between the four Nordic markets. If we impose the reasonable assumption that direct spillovers between the four Nordic markets are similar during the pre-crisis period and crisis period, ignoring the potential direct spillovers between the four Nordic markets would not affect the main findings of the study, since our definition of contagion compares the spillover effect during the pre-crisis period and crisis period. Future research could study the factors contributed to the lower discount rate and cash flow spillovers to the Nordic markets during the sovereign debt crisis.

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Equity Volatility Connectedness across China's Real Estate Firms and Financial Institutions

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Equity Volatility Connectedness across China's Real Estate Firms and Financial Institutions

Abstract:

The study investigates the dynamic equity volatility connectedness across the major real estate firms, banks, and other financial institutions in China. Based on the relative level of equity volatility connectedness, the study also examines the systemic importance of real estate firms and banks. The study shows that despite widespread worries about potential real estate bubbles in China, total directional connectedness from real estate firms to banks has decreased over the sample period. In contrast, total directional connectedness from banks to the real estate firms and to the financial institutions has become stronger over the sample period, which implies stronger risk originating from the banking sector. The study also shows that size plays an important role in determining the systemic importance of a real estate firm to the banking sector. The largest real estate firm displays the highest average systemic importance ranking. However, size does not appear to be the determinant factor of the systemic importance of a bank to the financial system. The largest bank shows the lowest average systemic importance ranking and 70% probability of being the least or second least systemically important bank in the long run.

Keywords: volatility connectedness; real estate firms; financial institutions; systemic importance
JEL classifications: G2, R3

1. Introduction

Real constant quality house prices in the major cities of China have more than doubled during the first decade of this century (Wu et al. 2012). Rapid house price growth has attracted numerous studies on the existence of potential real estate bubbles in China, and the findings are inconclusive. For instance, Feng and Wu (2015) do not find evidence of house price bubbles at the national level in China. However, they suggest that the conclusion could be sensitive to the expected income growth rate. Ren et al. (2012) conclude that there are no rational expectation bubbles in the Chinese housing market over the period 1999-2009. Using data from 1998 to 2010, Dreger and Zhang (2013) find some evidence of housing price bubbles in China, particularly in the southeast coastal areas and special economic zones.

Rather than focus on the existence of real estate bubbles that is difficult to determine, this study investigates the equity volatility connectedness across China's major real estate firms and financial institutions after the global financial crisis. More specifically, the study investigates the dynamic equity volatility connectedness between the real estate firms and banks, and that between the banks and financial institutions in China. Based on the relative level of equity volatility connectedness of each real estate firm to the banks and the relative level of equity volatility connectedness of each bank to the financial institutions, the study also examines the systemic importance of each real estate firm to the banking sector and the systemic importance of each bank to the financial system.

This investigation could have important policy implications. Firstly, equity volatility of real estate firms reflects the volatility of expected future cash flows, and the expected future cash flows for real estate firms are closely related to the expected real estate price. Therefore, volatility connectedness from real estate firms to banks, to some extent, measures the systemic risk contribution of the real estate market to the banking sector, which is an issue of particular importance to the policy makers in China. As highlighted by the recent subprime mortgage crisis, real estate market plays an important role in financial stability and the real economy. The boom and bust cycles in real estate contribute significantly to banking crises (see Allen and Carletti 2013 and references therein). At the end of 2015 China's real estate loans consist of 21.57% of the total bank loans (China Financial Stability Report 2016), and China's real estate sector also accounts for a crucial part of the economy's output (see e.g., Chan et al. 2016).

Secondly, the systemic risk of the banking sector is closely monitored by the Chinese policy makers, and the volatility or uncertainty connectedness between banks and the financial institutions provides a measure of the systemic risk contribution of the banking sector to the overall financial system. Thirdly, for monitoring and limiting systemic risk, it is essential to understand the dynamics of the systemic importance of real estate firms and banks. Furthermore, given the gradually increasing role of the Chinese economy in the world economy and the shifting of global systemically important banks from the developed economies to the emerging economies after the global financial crisis (Alessandri et al. 2015), the potential risks of China's real estate market and banks have significant implications for the global financial stability and economic growth.

The study mainly relates to two lines of previous research. One line of related research studies the volatility connectedness of financial institutions/markets or the linkages between securitized real estate and equity markets in the developed economies. For instance, Diebold and Yilmaz (2014) introduce measures of connectedness based on the forecast error variance decompositions and use these measures to study the equity volatility connectedness of 17 US financial institutions. Applying the same connectedness measures, Diebold and Yilmaz (2016) document the equity volatility connectedness of 35 major US and European financial institutions. Hoesli and Reka (2013) investigate the linkages among the local and international securitized real estate and equity markets in the US, UK and Australia. They provide evidence of stronger volatility spillovers between the securitized real estate and equity markets in the US than in the other two countries.

Another line of related research examines the systemic risk of financial institutions or the linkages between the real estate sector and other sectors in China. Gao and Ren (2013) construct a causal network for the Chinese financial system and show the importance of the most highly connected financial institutions in curbing systemic risk contagion. Focusing on the non-financial sectors, Chan et al. (2016) study the linkages between the real estate sector and other sectors in China. They find that real linkages between the real estate sector and other sectors in China have become stronger over time and credit risks of the real estate sector show large spillover effects on the other sectors. Huang et al. (2016) show that Chinese financial institutions' systemic risk contributions are related to their local network topology structure. They also show that the systemic risk contributions of the Chinese financial institutions tend to be persistent and small- and medium-sized commercial banks have larger average systemic risk contributions than the largest commercial banks. Li et al. (2016) analyze the full-sample static effect of the systemic risk in the real estate sector on banking return in China and show that higher systemic risk in the real estate sector leads to lower banking return. Huang et al. (2015) study the systemic risk of the listed commercial banks in China by four measures: conditional value at risk (CoVaR), marginal expected shortfall (MES), systemic impact index (SII) and vulnerability index (VI).

The study contributes to the previous literature in the following ways. Firstly, complementing previous research on the volatility connectedness of financial institutions in the developed economies, the study investigates the dynamic equity volatility connectedness between the real estate firms and banks in China. This investigation depicts the evolvements of the volatility or risk linkages between the real estate firms and banks, which is an issue of significant importance, given the critical role of the real estate and banking industry in economic development and financial stability. Secondly, previous research studying the systemic importance of financial institutions mainly focuses on the average rankings of systemic importance or the changes of average systemic importance rankings over different time periods (see e.g., Huang et al. 2015 and Huang et al. 2016). To our knowledge, this study is the first to systematically examine the transition behavior of the systemic importance ranking of the real estate firms and banks by discrete time Markov Chain model, which can provide more in-depth information on the characteristics of the evolving systemic importance of the real estate firms and banks.

The study finds that despite widespread worries about potential real estate bubbles in China, total directional connectedness from real estate firms to banks has decreased over the sample period. In contrast, total directional connectedness from banks to the real estate firms and to the financial institutions has become stronger over the sample period, which implies stronger risk originating from the banking sector. The study also shows that size plays an important role in determining the systemic importance of a real estate firm to the banking sector. The largest real estate firm displays the highest average systemic importance ranking. However, size does not appear to be the determinant factor of the systemic importance of a bank to the financial system. The largest bank shows the lowest average systemic importance ranking and 70% probability of being the least or second least systemically important bank in the long run.

The remainder of the study proceeds as follows. Section 2 describes the data and provides a brief overview of China's real estate and banking industry. Section 3 presents the method. Section 4 shows the empirical results and section 5 concludes the study.

2. Data and brief description of China's real estate and banking industry

Since the market-oriented reform in 1998, China's real estate industry went through significant development. However, rapid real estate price growth following the market-oriented reform, particularly after 2003, caused concern of the Chinese government, and to cool the overheating real estate market, Chinese government issued a series of regulatory policies, which includes land policies, tax policies and so on (see e.g., He 2016, 107–112). Now the real estate industry contributes significantly to the overall economy and the economic growth of China. On the other hand, China's banking industry is currently dominated by four big state-owned banks: Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China. These four state-owned banks were spun off from the People's Bank of China (PBC) in the late 1970s and 1980s. After a series of ownership structure reforms, the big four state-owned banks went public in the 2000s, changing the ownership structure from solely owned by the state to majorly owned by the state. To serve the economic policies and development, three policy banks were established in 1994, namely, China Development Bank, the Export-Import Bank of China, and Agricultural Development Bank of China. Another important part of China's banking industry is the (twelve) joint-stock banks. Apart from the big four state-owned banks, policy banks and joint-stock banks, China's banking industry includes numerous city commercial banks, rural commercial banks, rural cooperatives, and so on. A new player in China's banking industry is the private banks, which mainly support small- and medium-sized non-state-owned enterprises, as opposed to the state-owned lenders that favor lending to state-owned enterprises.

For the data, we retrieve from Datastream the daily high, low, opening and closing stock prices of the real estate firms and financial institutions in China. Seven real estate firms, ten banks, three broker-dealer firms and two insurance firms listed on the stock exchanges of Mainland China are included in the study (see table 1). We select the real estate firms based on the overall and wealth creation ability rankings of the top 10 listed real estate firms, which is published by China Real Estate TOP10 Research Group in 2016 (firms whose stocks suspended trading for long periods of time are excluded).[1] The selected real estate firms are among the largest ones in the Chinese real estate sector and receive relatively more media and investor attention. The ten banks considered in the study, which account for the major part of the Chinese banking industry, include the five largest commercial banks (the well-known 'big four' state-owned banks plus Bank of Communications) and five medium-sized commercial banks.[2] We include the largest three broker-dealer firms based on the total assets in 2015. The two insurance firms considered in the study are Ping An insurance and China Life insurance.

[Table 1 near here]

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[1] For the overall ranking, China Real Estate TOP10 Research Group evaluates a firm's size, wealth creation ability (economic value added), investment value, and financial soundness. For the wealth creation ability ranking, China Real Estate TOP10 Research Group assesses a firm's net operating profit after tax and cost of capital.

[2] PBC classifies a Chinese bank as a large bank if its total assets (including assets denominated in foreign currencies) exceed 2000 billion Yuan and a Chinese bank as a medium-sized bank if its total assets range from 300 billion Yuan to 2000 billion Yuan (PBC makes the classifications based on the total assets of a bank at the end of 2008, see the 2015 Annual Report of PBC, pp. 92–93). According to the above classifications, PBC lists the following seven banks as large Chinse banks: Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, Bank of China, China Development Bank, Bank of Communications, and Postal Savings Bank of China (see the 2015 Annual Report of PBC, p. 92). We include all the large Chinese banks, except for China Development Bank and Postal Savings Bank of China (As of Q1 2017, China Development Bank and Postal Savings Bank of China are not listed on the stock exchanges of Mainland China). Similarly, PBC registers fourteen Chinese banks as medium-sized banks (see the 2015 Annual Report of PBC, p. 93), and we select the first five relatively larger public banks.

The sample period of the study, determined by the data availability of the selected firms, ranges from September 2, 2010 to December 18, 2015.[3] Excluding days when some of the sample firms were not trading or when some of the sample firms' range-based volatility estimate is zero, the final sample contains 1065 daily observations. As in Diebold and Yilmaz (2016), we use the method of Garman and Klass (1980) to calculate the range-based volatility estimate and transform the volatility estimate into log volatility.

3. Method

To study the equity volatility connectedness of the selected real estate firms and financial institutions, we follow the methodology of Diebold and Yilmaz (2014). Suppose an *N*-dimensional vector x_t follows a covariance-stationary VAR(*p*) process and has the following infinite moving average representation:

$$x_t = \Sigma_{l=0}^{\infty} A_l \varepsilon_{t-l}, \qquad (1)$$

where ε_t is an *N*-dimensional error term with mean zero and covariance matrix Σ. The generalized *H*-step ahead forecast error variance decomposition of variable *i* due to innovations in variable *j* is

$$d_{ij}^{gH} = \sigma_{jj}^{-1} \Sigma_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2 / \Sigma_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i), \qquad (2)$$

[3] Agriculture Bank of China went public on July 15, 2010. The stock of Ping An insurance suspended trading from July 15, 2010 to September 1, 2010. As the largest real estate firm in China Vanke's stock suspended trading from December 19, 2015 to July 1, 2016. When we exclude Vanke and extend the sample period to the end of March 2017, the results of the dynamic volatility connectedness (available upon request) show that there is some increase for the total directional connectedness from real estate firms to banks from March 2016 to July 2016. The connectedness measure then starts to decrease and at the end of sample period it reaches a level much lower than that of the beginning of the sample period. On the other hand, total directional connectedness from banks to real estate firms stands at a relatively high level in 2016 and only starts to decrease until the end of 2016. The connectedness from banks to real estate firms at the end of the sample period is similar to that of the beginning of the sample period. Total directional connectedness from banks to all the financial institutions starts to decrease at the end of 2015 and at the end of the sample period it is still above that of the beginning of the sample period.

where e_i is an N-dimensional column vector with the ith element equal to one and zeros elsewhere, and σ_{jj} is the jth diagonal element of Σ.

Based on the forecast error variance decompositions, Diebold and Yilmaz (2014) define the pairwise directional connectedness as

$$C^H_{i\leftarrow j} = d^{gH}_{ij}. \qquad (3)$$

Aggregating the pairwise directional connectedness, they define total directional connectedness from others to i as

$$C^H_{i\leftarrow \cdot} = \Sigma^N_{j=1,j\neq i} d^{gH}_{ij}, \qquad (4)$$

total directional connectedness to others from j as

$$C^H_{\cdot\leftarrow j} = \Sigma^N_{i=1,i\neq j} d^{gH}_{ij}, \qquad (5)$$

and total connectedness as

$$C^H = \Sigma^N_{i,j=1,i\neq j} d^{gH}_{ij}/N. \qquad (6)$$

As in Diebold and Yilmaz (2014), we normalize the generalized forecast error variance decompositions by defining $\tilde{d}^{gH}_{ij} = d^{gH}_{ij}/\Sigma^N_{j=1} d^{gH}_{ij}$ and compute the connectedness measures based on $\tilde{d}^{gH}_{ij}$.

Diebold and Yilmaz (2014) show that the above connectedness measures are closely related to the systemic risk measures and to the connectedness measures in network theory. Specifically, the total directional connectedness ‘from’ is closely related to the marginal expected shortfall of Acharya et al. (2010) and the total directional connectedness ‘to’ is closely related to the CoVaR of Adrian and Brunnermeier (2011); with the forecast error variance decomposition matrix defining a weighted directed network, the total connectedness corresponds to the mean network degree and the total directional connectedness corresponds to the node degree in network theory.

One may notice that all the connectedness measures are based on the forecast error variance decompositions which show the proportions of fluctuation (forecast error variance) in a variable due to shocks in other variables in the system. For example, directional connectedness from real estate firms to banks shows the proportions of fluctuation in the volatility or risk of banks that can be attributed to shocks in the volatility or risk of the real estate firms. Hence, directional connectedness from real estate firms to banks provides an intuitive way to measure the risk contribution of the real estate firms to banks. Analogously, directional connectedness from banks to all the financial institutions aggregates the risk contribution of banks to all the financial institutions.

4. Results

In this section we present the empirical results. Following Diebold and Yilmaz (2016), we estimate vector autoregressive models of order 3 and compute the volatility connectedness based on the 12 days ahead forecast error variance decompositions.

4.1. Static (full-sample) connectedness

We first present the results of the static full-sample volatility connectedness. To conserve space, we do not report the entire pairwise directional connectedness table of the 22 firms. Instead, we only describe the main features of the pairwise directional connectedness table. Volatility connectedness among the same type of firms is generally higher than that among different types of firms. The largest pairwise directional connectedness is observed between two broker-dealer firms: volatility connectedness from Haitong Securities to Citic Securities is 9.94% and that from Citic Securities to Haitong Securities is 9.17%. Two pairs of real estate firms and banks also show large volatility connectedness: volatility connectedness from Poly Real Estate to Vanke is 9.23% and that from Vanke to Poly Real Estate is 8.40%; volatility connectedness from Shanghai Pudong Development Bank to Industrial Bank is 8.84% and that from Industrial Bank to Shanghai Pudong Development Bank is 8.37%. The higher volatility connectedness for firms within the same sector suggests that there is a sector-specific factor affecting the volatilities of all firms in the same sector. The top three real estate firms showing the highest volatility connectedness to the banks are Poly Real Estate, Financial Street Holdings, and Vanke; the top three banks showing the highest volatility connectedness to the financial institutions (banks and other financial institutions) are Shanghai Pudong Development Bank, China Merchants Bank, and Industrial Bank. The high volatility connectedness of these three real estate firms to the banks indicates their importance to the stability of the banking sector, and the high volatility connectedness of these three banks to the financial institutions indicates their systemic importance to the financial system.

We also aggregate the pairwise directional connectedness among three ‘sectors’: a sector of real estate firms, a sector of banks, and a sector of other financial institutions. Table 2 shows that total volatility connectedness among firms in the same sector is larger than that in different sectors, except for the sector of other financial institutions which has larger connectedness from the banking sector. For the sector of real estate firms, total directional connectedness from the financial institutions is about 50% (341.13%/7), indicating the high impact of the financial sector on the real estate sector, especially the high impact of the banks. For the banking sector, total volatility connectedness from the real estate sector is about 15% (149.46%/10). For the sector of other financial institutions, the large connectedness from the banking sector results from the close linkages between banks and other financial institutions and the relatively larger number of banks than other financial institutions (ten banks versus five other financial institutions).

[Table 2 near here]

With a net directional connectedness of -104.77%, the real estate sector is a net receiver of volatility connectedness. In contrast, the banking sector is a net transmitter of volatility connectedness to the other two sectors and the sector of other financial institutions balances its connectedness from and to the other two sectors. Finally, the total connectedness of 82.78% across the 22 firms in our study is very close to the corresponding number of 81.7% across the 28 US and European financial institutions in the study of Diebold and Yilmaz (2016).

4.2. Dynamic (rolling-sample) connectedness

The static full-sample analysis above provides an average measurement of the connectedness among the real estate and financial firms over the whole the sample period. However, from the perspective of economic monitoring, dynamic rolling-sample connectedness could be more useful in providing real-time measurement of the connectedness among the real estate and financial firms. Fig. 1 shows the evolution of the rolling-sample connectedness. Following expectations of slower economic growth, total connectedness decreases from above 80% at the end of 2011 to below 70% at the end of 2012, after which it gradually increases (see Fig. 1 (a)). On September 29, 2013 Shanghai Free Trade Zone was established and stock prices of firms perceived to benefit from the newly established trade zone were pushed to very high levels. At the same time, total connectedness increases to around 85%, after which it starts a downward trend, reaching the lowest level of around 71% at the end of July 2014. Total connectedness across the 22 firms remains relatively stable from August to November 2014. On November 17, 2014 Shanghai-Hong Kong stock connect (or Hu-Gang Tong) officially began, and total connectedness jumps from around 73% in late November to around 84% at the beginning of December. Total connectedness continues to increase and reaches the highest level of above 90% during the stock market crashes in the summer of 2015. Total connectedness then starts to decrease slowly at the end of September and finally stands at around 87% at the end of the sample period.

[Figure 1 near here]

From late 2009 to the beginning of 2011 Chinese government issued a series of regulations aimed at cooling the overheating real estate market. These regulations may have contributed to the more than 50% decrease in the total directional connectedness from real estate firms to banks over the period from late 2011 to the beginning of 2013 (see Fig. 1 (b)). Total directional connectedness from real estate firms to banks then rises steadily, and by August 2013 it has almost reverted back to the initial value of 200% in late 2011. Then the total directional connectedness goes through a similar cycle: it first moves downward and then gradually moves upward. After reaching the highest level of 243% in late June 2015, the total directional connectedness starts to move downward. At the end of the sample period, total directional connectedness from real estate firms to banks stays at 169%, about 15% lower than the initial value of 200%.

Except for a short period in the summer of 2015, total directional connectedness from real estate firms to banks during the sample period has always stayed at a level lower than the initial value of 200% in late 2011. Therefore, despite widespread worries about potential real estate bubbles in China, total directional connectedness from real estate firms to banks has actually decreased over the sample period. Since the performance of real estate firms is closely tied to the real estate market, the observed connectedness from real estate firms to banks also suggests that systemic risk contribution of the real estate market to the banking industry, as perceived by the market participants, does not seem to pose a threat to the stability of the banking industry by the end of the investigation period.

In contrast to the weakening connectedness from real estate firms to banks, the connectedness from banks to real estate firms has become stronger over the sample period (see Fig. 1 (b)). From late 2011 to November 2014, the general trend of total directional connectedness from banks to real estate firms is similar to that from real estate firms to banks. After a jump from around 130% in late November to above 200% at the beginning of December 2014, total directional connectedness from banks to real estate firms shows an upward trend and by the end of the sample period, it reaches a level of around 300%. Over the sample period, the connectedness from banks to real estate firms increases by about 40%. As the total directional connectedness from banks to real estate firms is always above that from real estate firms to banks, net total directional connectedness from banks to real estate firms is always positive, especially at the end of the sample period.

Similar to the total directional connectedness from banks to real estate firms, total directional connectedness from banks to all the financial institutions (including the connectedness across different banks) shows an upward trend in the latter part of the sample period: it rises from around 600% in September 2014 to above 800% in December 2015 (see Fig. 1 (c)). In the earlier part of the sample period, total directional connectedness from banks to the financial institutions remains relatively stable, except for a large fluctuation from December 2012 to August 2013 and a large drop from June 2014 to August 2014. Over the sample period, total directional connectedness from banks to the financial institutions increases by about 27%.

The strengthening connectedness from banks to the real estate firms and to the financial institutions implies the increasing systemic risk of the banking industry, which is consistent with the market concerns about the rising nonperforming loans accompanying the slowing economic growth in China. According to China Banking Regulatory Commission (CBRC), the ratio of non-performing loans for the commercial banks has been increasing consistently from 0.96% in the first quarter of 2013 to 1.75% in the second quarter of 2016. The official statistics of CBRC may have underestimated the situation of the banking industry. A recent report by International Monetary Fund (IMF) suggests that Chinese banks' potential loan losses could be as high as 7% of GDP (IMF 2016).

[Figure 2 near here]

As in Diebold and Yilmaz (2016), the dynamic connectedness in this section is computed based on forecast error variance decompositions with a rolling window of 200 days and a forecast horizon of 12 days. We also examine the robustness of the results to a different length of rolling window or forecast horizon. Fig. 2 shows the total connectedness when we change the rolling window length to 150 days or the forecast horizon to 6 days. Three features can be observed from Fig. 2. First, total connectedness shows similar trend under the benchmark case and the two robust cases. Second, total connectedness remains quantitatively similar when the forecast horizon is changed to 6 days. Third, total connectedness becomes more volatile when the rolling window length is changed to 150 days. These features can also be observed for the total directional connectedness across the real estate firms, banks and financial institutions (results available upon request). Thus, the general results of the dynamic connectedness remain robust.

4.3. Systemic importance rankings based on the dynamic connectedness

In the section above we analyze the overall dynamic connectedness from real estate firms to banks and that from banks to all the financial institutions. In this section we study the dynamic connectedness from each individual real estate firm to all the banks and that from each individual bank to all the financial institutions. In particular, for each day during the sample period, we rank the systemic importance of each real estate firm to the banking industry by comparing the levels of connectedness from each individual real estate firms to all the banks; in a similar way, for each day during the sample period, we rank the systemic importance of each bank to the financial system by comparing the levels of connectedness from each individual banks to all the financial institutions (excluding the own-connectedness of a bank). For a real estate firm or bank, we are interested in its ranking of systemic importance and its behavior of migration between different rankings.

[Table 3 near here]

Table 3 shows the average ranking of systemic importance for all the real estate firms and banks. Vanke (VK), Poly Real Estate (PRE), and Financial Street Holdings (FSH) are the top three real estate firms showing the highest systemic importance to the banking industry, while China Fortune Land Development (CFLD) has the lowest ranking of systemic importance to the banking industry. On the other hand, Shanghai Pudong Development Bank (SPDB), Bank of

Communications (BC), and Industrial Bank (IB) are the three banks with the highest ranking of systemic importance to the financial system. Interestingly, Industrial and Commercial Bank of China (ICBC), which is the largest Chinese bank, shows the lowest ranking of systemic importance to the financial system, i.e., volatility connectedness from ICBC to the financial system is, on average, the lowest among the ten banks. This finding of systemic importance for the banks is consistent with Huang et al. (2015) and Huang et al. (2016). Studying the systemic risk contributions of all the listed financial institutions in China, Huang et al. (2016) show that ICBC is the bank with the lowest average systemic risk contribution, while SPDB, IB and China Merchants Bank (CMEB) are the three banks with the highest average systemic risk contribution, although BC and CMEB have very close value of average systemic risk contribution.

The average rankings of systemic importance for the banks in Table 3 suggest that medium-sized banks appear to show higher rankings of systemic importance (or larger systemic risk contribution), whereas the largest banks show smaller systemic risk contributions. Thus, as suggested by Alessandri et al. (2015), size may not be the most significant determinant factor of a bank's systemic importance; complexity and substitutability could contribute more to the systemic importance of a bank. However, size does seem to play an important role in determining the systemic importance of a real estate firm to the banking sector: larger real estate firms tend to have higher rankings of systemic importance to the banking sector (e.g., as the largest real estate firm in China, Vanke has the highest ranking of systemic importance to the banking sector)[4].

[Table 4 near here]

[4] For instance, at the end of 2015 total assets and total borrowings for the real estate firms are (units: billion Yuan; total assets and total borrowings for FSH are the values at the beginning of 2016): VK (611.30 and 35.73), PRE (403.83 and 69.51), CFLD (168.62 and 27.60), FSH (105.68 and 33.27), GE (139.35 and 14.15), SH (244.25 and 69.82), and CP (55.32 and 18.65).

Taking as states the rankings of systemic importance, we also study the transition of the systemic importance ranking of each real estate firm and bank by a simple discrete time Markov Chain model. Such a study could provide insight into the way the ranking of systemic importance of a real estate firm or bank changes between different time periods. Tables 4 and 5 report the estimates of the matrix of transition probabilities for the real estate firm and bank with the highest average systemic importance: Vanke and SPDB (estimates of the matrix of transition probabilities for the other real estate firms and banks are available upon request). The (i, j)th element of the transition probabilities matrix shows the probability that the real estate firm (or bank) will be the jth systemically important real estate firm (or bank) next day, given that it is the ith systemically important real estate firm (or bank) today. The systemic importance ranking of Vanke and SPDB during the sample period ranges from 1 to 5 and 1 to 9, respectively. Large diagonal elements in Table 4 suggest that the systemic importance rankings of Vanke are highly persistent. For instance, if Vanke were observed to be the most systemically important real estate firm today, the probability that it will also be the most systemically important real estate firm tomorrow is 96%. However, as the systemic importance rankings in the middle (ranking 2, 3, and 4) have smaller diagonal elements, a middle-level systemic importance is more likely to transit to another level. When the ranking of systemic importance changes, it is more likely to change to the 'neighboring' rankings of systemic importance, as the transition probabilities closer to the diagonal are generally larger. Moreover, only when Vanke ranks second or third in systemic importance can it transit to the most systemically important real estate firm in one step (or one day). The above characteristics of transition probabilities for Vanke are also found for SPDB, except that SPDB has a high probability of moving to the 8th systemically important bank when its current systemic importance ranking is 9 (see table 5).

[Table 5 near here]

Table 6 presents the long-run probabilities of being in each systemic importance rankings and the mean first passage time between the lowest ranking and the highest ranking for each real estate firm. The long-run probabilities (the fixed probability vector) are the probabilities of being in the different systemic importance rankings in the long run. The mean first passage time from ranking *i* to ranking *j* is the expected number of steps (days) to reach ranking *j* for the first time, starting at ranking *i*. Since the transitions between neighboring rankings are more likely, the mean first passage time between the lowest ranking and the highest ranking generally provides the maximum mean first passage time between any two rankings. Table 6 shows that in the long run PRE and VK have the highest probability (43% and 30%) of being the most systemically important real estate firm. In addition, VK also has a high probability of being the second or the third systemically important real estate firm. In contrast, CFLD has the highest probability (68%) of being the least systemically important real estate firm, and it takes relatively less time (38.42 days) for CFLD to go from its highest ranking of 3 to its lowest ranking of 7. The expected number of days to transit from the lowest ranking to the highest ranking for PRE and VK is 79.25 days and 82.20 days, respectively. The expected number of days for Gemdale (GE) to transit from its lowest ranking to its highest ranking, by contrast, is 931.40 days.

[Table 6 near here]

Table 7 shows the long-run probabilities of being in each systemic importance rankings and the mean first passage time between the lowest ranking and the highest ranking for each bank. BC and SPDB show the highest probability (35% and 17%) of being the most systemically important bank. Moreover, SPDB also shows the highest probability (29%) of being the second most systemically important bank. On the other hand, ICBC shows the highest probability (41% and 29%) of being the least or second least systemically important bank, and it also takes relatively less time (76.31 days) for ICBC to migrate from its highest ranking of 3 to its lowest ranking of 10. BC takes the longest time to reach its lowest ranking from its highest ranking and SPDB takes the shortest time to transit from its lowest systemic importance ranking to its highest systemic importance ranking.

[Table 7 near here]

Two issues could be noted. In the study we use a relatively small number of real estate firms to represent the real estate sector in China and thus one issue is whether the real estate sector can be represented by the selected real estate firms. We argue that our sample of real estate firms provides a reasonable representation of the Chinese real estate sector for two reasons. First, the analyzed real estate firms are among the largest ones in the Chinese real estate sector and receive relatively more media and investor attention. Second, section 4.1 suggests the existence of a sector-specific factor affecting the volatilities of all firms in the same sector. Volatilities of the largest firms in a sector could largely capture the sector-specific factor. The above arguments also apply to the issue of whether the financial system in China can be represented by the analyzed financial institutions.[5]

As in Diebold and Yilmaz (2016), in the study we analyze the overall volatility rather than the idiosyncratic volatility of a firm. The overall volatility contains a common market-wide component which would increase the volatility connectedness of the firms included in the study.

[5] We also examine the robustness of the results when small and medium-sized real estate firms and banks are added to the sample firms. We include three additional firms listed on the Small and Medium Enterprise Board of Shenzhen Stock Exchange: two real estate firms (Cosmos Group and Hangzhou Binjiang Real Estate Group) and one bank (Bank of Ningbo). The results (available upon request) show that the main findings of the study remain unchanged.

However, since we work with log volatility, the effect of the common component would be small if the ratio of the common component to the overall volatility is approximately constant over the sample period.

5. Conclusion

The study investigates the dynamic equity volatility connectedness across the major real estate firms, banks, and other financial institutions in China. Based on the relative level of equity volatility connectedness of each real estate firm (each bank) to the banks (the financial institutions), the study also examines the systemic importance of each real estate firm to the banking sector and the systemic importance of each bank to the financial system.

The study shows that total directional connectedness from real estate firms to banks has decreased over the sample period, which implies lower risk of the real estate sector to the banking sector. On the other hand, total directional connectedness from banks to the real estate firms and to the financial institutions has become stronger over the sample period, implying stronger risk of the banking sector to the real estate sector and the financial system. The study also shows that size plays an important role in determining the systemic importance of a real estate firm to the banking sector. The largest real estate firm displays the highest average systemic importance ranking. However, size does not appear to be the determinant factor of the systemic importance of a bank to the financial system. Medium-sized banks show higher average ranking of systemic importance. The largest bank shows the lowest average ranking of systemic importance and 70% probability of being the least or second least systemically important bank in the long run, and whenever it is not the least systemically important bank, it takes less than 77 days (on average) to return to the status of least systemically important bank. Future research could examine the factors contributing to the decreasing connectedness from real estate firms to the banks and the increasing connectedness from banks to the financial institutions over the sample period.

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Table 1. The real estate firms and financial institutions included in the analysis.

Firm no.	Stock code	Firm name
1	000002.SZ	VANKE (VK)
2	600048.SH	POLY REAL ESTATE (PRE)
3	600340.SH	CHINA FORTUNE LAND DEVELOPMENT (CFLD)
4	000402.SZ	FINANCIAL STREET HOLDINGS (FSH)
5	600383.SH	GEMDALE (GE)
6	600823.SH	SHANGHAI SHIMAO (SH)
7	000031.SZ	COFCO PROPERTY (CP)
8	601288.SH	AGRICULTURAL BANK OF CHINA (ABC)
9	601328.SH	BANK OF COMMUNICATIONS (BC)
10	601398.SH	INDUSTRIAL AND COMMERCIAL BANK OF CHINA (ICBC)
11	601939.SH	CHINA CONSTRUCTION BANK (CCB)
12	601988.SH	BANK OF CHINA (BOC)
13	600000.SH	SHANGHAI PUDONG DEVELOPMENT BANK (SPDB)
14	600016.SH	CHINA MINSHENG BANK (CMIB)
15	600036.SH	CHINA MERCHANTS BANK (CMEB)
16	601166.SH	INDUSTRIAL BANK (IB)
17	601998.SH	CHINA CITIC BANK (CCIB)
18	600030.SH	CITIC SECURITIES
19	600837.SH	HAITONG SECURITIES
20	000776.SZ	GF SECURITIES
21	601318.SH	PING AN INSURANCE
22	601628.SH	CHINA LIFE INSURANCE

Notes: the table shows the name and stock code of the firms included in the study. Abbreviations of firm names for the real estate firms and banks are shown in the parentheses. Firm no. 1-7 are the analyzed real estate firms, firm no. 8-17 are the analyzed banks, firm no. 18-20 are the analyzed broker-dealer firms, and firm no. 21-22 are the analyzed insurance firms.

Table 2. Full-sample connectedness.

	Real estate firms	Banks	Other financial institutions	FROM
Real estate firms	358.87	226.83	114.30	341.13
Banks	149.46	661.94	188.61	338.06
Other financial institutions	86.90	209.29	203.82	296.18
TO	236.35	436.12	302.90	
NET	-104.77	98.06	6.72	**82.78**

Notes: the table aggregates the pairwise directional connectedness among the real estate firms, banks and other financial institutions (broker-dealer and insurance firms). The sample of firms is divided into three 'sectors': a sector of real estate firms, a sector of banks, and a sector of other financial institutions. The *ij*-th element of the upper-left 3-by-3 matrix shows the total pairwise directional connectedness of firms in sector *j* to firms in sector *i* (the diagonal element also includes the own-connectedness of each firm in a sector). The last column FROM is the sum of the elements in each row and the second last row TO is the sum of the elements in each column, excluding the elements in the diagonal. The last row NET shows the difference between total directional connectedness FROM and total directional connectedness TO for each sector. The bottom right number (in boldface) is the total connectedness among the 22 firms.

Table 3. Average ranking of systemic importance for the real estate firms and banks.

Panel A: Average ranking of real estate firms										
Firm name	VK	PRE	CFLD	FSH	GE	SH	CP			
Average ranking	2.41	2.67	6.48	3.31	4.38	4.23	4.53			
Panel B: Average ranking of banks										
Firm name	ABC	BC	ICBC	CCB	BOC	SPDB	CMIB	CMEB	IB	CCIB
Average ranking	6.44	3.48	8.86	6.62	6.12	3.17	4.49	4.61	4.31	6.89

Notes: firstly, we compute the dynamic pairwise directional connectedness of the 22 firms based on a rolling window of 200 days and a forecast horizon of 12 days. Then, for each day during the sample period, we compute the directional connectedness of each real estate firm to the banks, and the directional connectedness of each bank to all the financial institutions (excluding the own-connectedness of a bank). Finally, for a given day during the sample period, we rank the systemic importance of each real estate firm to the banking sector by comparing the levels of the directional connectedness of each real estate firm to the banks on that day: the real estate firm with the highest directional connectedness to the banks on that day is ranked 1st, the real estate firm with the second highest directional connectedness to the banks on that day is ranked 2nd, and so on. In a similar way, for a given day during the sample period, we rank the systemic importance of each bank to the financial system by comparing the levels of the directional connectedness of each bank to all the financial institutions on that day: the bank with the highest directional connectedness to the financial institutions on that day is ranked 1st, the bank with the second highest directional connectedness to the financial institutions on that day is ranked 2nd, and so on. After ranking the systemic importance of each real estate firm and each bank on each day, we obtain a sequence of rankings for each real estate firm and bank. Table 3 shows the average of the rankings for the real estate firms and banks. See table 1 for the abbreviation of the firm names.

Table 4. Estimates of transition probabilities matrix for Vanke.

	K1	K2	K3	K4	K5
K1	0.96*	0.03*	0.01	0.00	0.00
K2	0.03*	0.85*	0.09*	0.02	0.00
K3	0.01	0.14*	0.77*	0.08*	0.01
K4	0.00	0.01	0.15*	0.83*	0.02
K5	0.00	0.02	0.02	0.03	0.93*

Notes: with the sequence of rankings for each real estate firm (see the notes below table 3), we model the transition of the systemic importance ranking of each real estate firm by a simple discrete time Markov chain model, taking as states the rankings of the systemic importance. Table 4 reports the maximum likelihood estimates of the transition probabilities matrix for one of the real estate firms: Vanke. 'Ki' denotes the systemic importance ranking *i*. The (*i*, *j*)th element of the transition probabilities matrix shows the probability that Vanke will be the *j*th systemically important real estate firm next day, given that it is the *i*th systemically important real estate firm today. '*' indicates that the lower bound of the 95% confidence interval for the corresponding transition probability is above zero.

Table 5. Estimates of transition probabilities matrix for SPDB.

	K1	K2	K3	K4	K5	K6	K7	K8	K9
K1	0.88*	0.12*	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K2	0.06*	0.86*	0.07*	0.01	0.00	0.00	0.00	0.00	0.00
K3	0.02	0.17*	0.71*	0.08*	0.02	0.00	0.00	0.00	0.00
K4	0.00	0.01	0.06*	0.78*	0.13*	0.02	0.00	0.00	0.00
K5	0.00	0.00	0.03	0.28*	0.59*	0.04	0.06*	0.00	0.00
K6	0.00	0.00	0.00	0.05	0.13*	0.56*	0.26*	0.00	0.00
K7	0.00	0.00	0.02	0.00	0.02	0.19*	0.75*	0.02	0.02
K8	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.83*	0.08
K9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.60*

Notes: with the sequence of rankings for each bank (see the notes below table 3), we model the transition of the systemic importance ranking of each bank by a simple discrete time Markov chain model, taking as states the rankings of the systemic importance. Table 5 reports the maximum likelihood estimates of the transition probabilities matrix for one of the banks: SPDB. 'Ki' denotes the systemic importance ranking *i*. The (*i*, *j*)th element of the transition probabilities matrix shows the probability that SPDB will be the *j*th systemically important bank next day, given that it is the *i*th systemically important bank today. '*' indicates that the lower bound of the 95% confidence interval for the corresponding transition probability is above zero.

Table 6. Long-run probabilities and mean first passage time for the real estate firms.

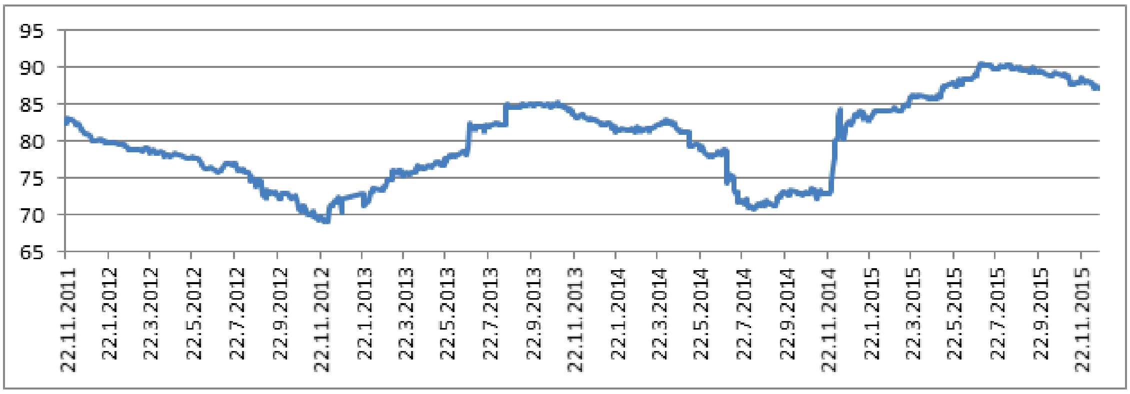
	Long-run probabilities of being in each ranking							Mean first passage time	
	K1	K2	K3	K4	K5	K6	K7	H to L	L to H
VK	0.30	0.27	0.22	0.14	0.07			236.78	82.20
PRE	0.43	0.16	0.09	0.10	0.06	0.15	0.01	459.68	79.25
CFLD			0.01	0.04	0.15	0.11	0.68	38.42	351.87
FSH	0.14	0.20	0.21	0.19	0.18	0.04	0.03	535.89	133.51
GE	0.00	0.15	0.18	0.24	0.13	0.25	0.05	210.30	931.40
SH	0.11	0.06	0.11	0.17	0.31	0.20	0.03	160.06	228.19
CP	0.02	0.15	0.17	0.12	0.10	0.26	0.19	144.22	266.53

Notes: the table reports the long-run probabilities of being in each systemic importance ranking and the mean first passage time between the lowest ranking and the highest ranking, based on the estimates of the matrix of transition probabilities for each real estate firm (see the notes below table 4). 'Ki' denotes the systemic importance ranking *i*. 'H to L' denotes the mean first passage time from the highest ranking to the lowest ranking. 'L to H' denotes the mean first passage time from the lowest ranking to the highest ranking. The highest ranking of the real estate firms is 1, except for CFLD whose highest ranking is 3. The lowest ranking of the real estate firms is 7, except for VK whose lowest ranking is 5 (see table 1 for the abbreviation of the real estate firm names).

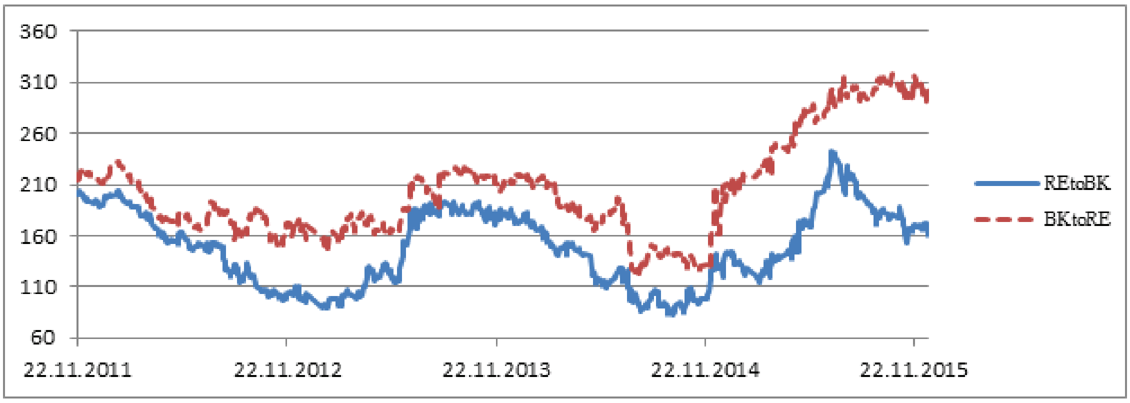
Table 7. Long-run probabilities and mean first passage time for the banks.

	Long-run probabilities of being in each ranking										Mean first passage time	
	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	H to L	L to H
ABC	0.00	0.06	0.11	0.07	0.09	0.13	0.17	0.20	0.09	0.08	209.13	852.22
BC	0.35	0.06	0.15	0.12	0.07	0.09	0.11	0.04	0.01	0.00	1329.86	158.11
ICBC			0.01	0.01	0.03	0.08	0.04	0.11	0.29	0.41	76.31	1194.42
CCB	0.11	0.16	0.14	0.08	0.05	0.05	0.04	0.06	0.12	0.19	559.21	447.37
BOC	0.11	0.07	0.03	0.07	0.08	0.11	0.19	0.14	0.15	0.05	369.27	622.93
SPDB	0.17	0.29	0.11	0.17	0.08	0.05	0.08	0.03	0.01		637.62	115.89
CMIB	0.06	0.13	0.16	0.17	0.15	0.15	0.11	0.05	0.01		253.99	337.15
CMEB	0.07	0.10	0.19	0.14	0.13	0.04	0.02	0.12	0.16	0.04	370.58	377.75
IB	0.14	0.14	0.10	0.10	0.22	0.13	0.05	0.10	0.02		348.30	274.57
CCIB		0.02	0.02	0.06	0.10	0.17	0.19	0.19	0.11	0.13	131.57	333.16

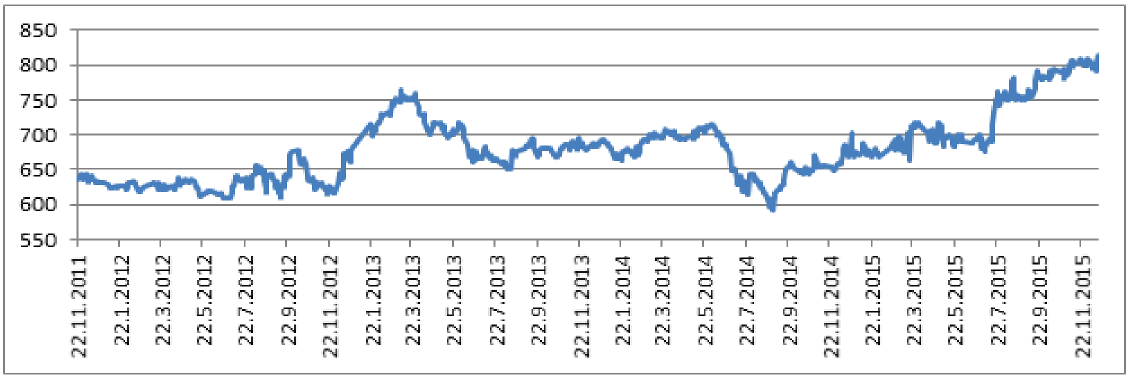
Notes: the table reports the long-run probabilities of being in each systemic importance ranking and the mean first passage time between the lowest ranking and the highest ranking, based on the estimates of the matrix of transition probabilities for each bank (see the notes below table 5). 'Ki' denotes the systemic importance ranking *i*. 'H to L' denotes the mean first passage time from the highest ranking to the lowest ranking. 'L to H' denotes the mean first passage time from the lowest ranking to the highest ranking. The highest ranking of the banks is 1, except for ICBC and CCIB whose highest ranking is 3 and 2, respectively. The lowest ranking of the banks is 10, except for SPDB, CMIB and IB whose lowest ranking is 9 (see table 1 for the abbreviation of the bank names).



(a). Total connectedness.



(b). Total directional connectedness between real estate firms and banks. ‘REtoBK’ is the connectedness from real estate firms to banks and ‘BKtoRE’ is the connectedness from banks to real estate firms.



(c). Total directional connectedness from banks to all the financial institutions.

Figure 1. Dynamic connectedness. The dynamic connectedness is computed based on a rolling window of 200 days and a forecast horizon of 12 days.

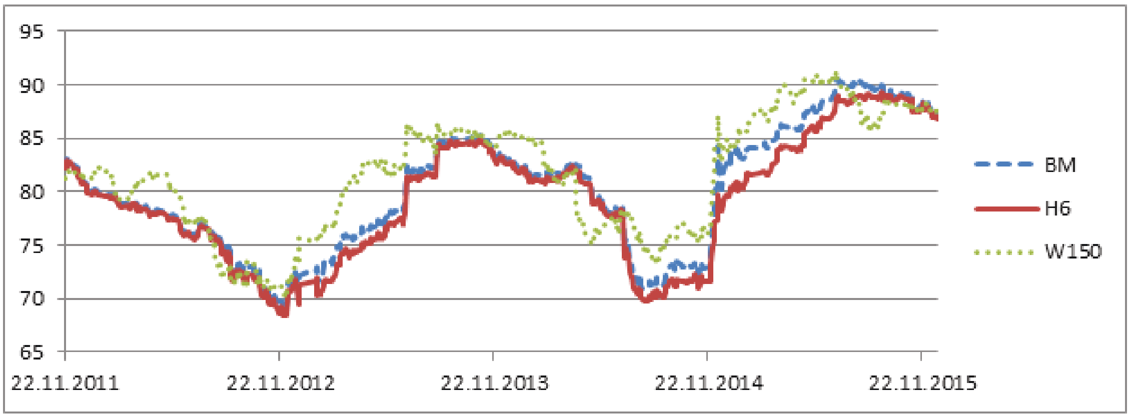


Figure 2. Dynamic total connectedness. 'BM' is the benchmark case total connectedness; 'H6' is the total connectedness when the forecast horizon of variance decompositions is changed to 6 days; 'W150' is the total connectedness when the rolling-window length is changed to 150 days.

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Frequency volatility connectedness across different industries in China

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A B S T R A C T

Utilizing the advantageous method of Barunik and Krehlik (2018), we examine the frequency connectedness of equity volatilities across 12 industries in China from October 2003 to April 2018. The results indicate that the main targets of risks in China are Banking and Real Estate, while the main sources of risks are Construction and Materials, Industrial Transportation, and Chemicals. The study also highlights the importance of the use of frequency connectedness method such that the main targets and sources of risks at different frequencies over different time periods can be detected, providing essential information for the monitoring of the financial market.

1. Introduction

After four decades of fast economic growth, China is nowadays the second largest economy in the world with an increasingly central role for the global economy. Recent literature shows that certain Chinese industries such as Banking and manufacturing-related industries are perceived to have significant implications for the global financial and economic stability. For example, Alessandri et al. (2015) find that after the Global Financial crisis, global systemically important banks shifted from the developed economies to the emerging economies, particularly China. This finding implies that the Banking industry in China has become an important part of the global financial system. In similar vein, Baum et al. (2015) show that macroeconomic announcements related to Chinese manufacturing and industrial output (purchasing manager index, industrial production, and real GDP) are viewed as barometers of the state of the world economy, affecting equity, commodity, and currency markets. Furthermore, recent literature also suggests that intersectoral linkages of Chinese industries are of high importance for maintaining its own financial and economic stability. For instance, Chan et al. (2016) show that due to intersectoral linkages, Real Estate sector has large credit risks spillovers to 13 other sectors in China and contributes significantly to the economic output.

The purpose of this study is to examine which Chinese industries are the main sources of risks and which are most susceptible targets of risks in terms of equity volatility connectedness. Equity volatility connectedness can be used to show which industries are the main receivers of volatility spillovers (i.e. the main targets of risks) and which industries are the main transmitters of volatility spillovers (i.e. the main sources of risks) from the perspective of market participants. This is an important task, given the significant role of certain industries in China (e.g., Banking and manufacturing-related industries). For this purpose, we use an advantageous approach of Barunik and Krehlik (2018) and analyze the equity volatility connectedness at different frequencies (short, medium, and

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long term), which is important for portfolio construction, risk management, and the monitoring of financial risks. For instance, for portfolio construction, investors with (short) long investment horizons may focus on the (short-term) long-term volatility connectedness between two industries. In addition, high long-term volatility connectedness across different industries suggests that shocks to the industries are persistent and have long-term impact on the system. Hence, for monitoring financial risks, policy makers should pay more attention to shocks that cause jumps in long-term volatility connectedness across industries, as those shocks create large long-term impact on the system.

There is increasing number of studies that examine the connectedness of volatilities across different financial markets or financial institutions (e.g. international stock markets, Diebold and Yilmaz, 2009; sovereign bond markets, Fernandez-Rodriguez et al., 2016; cryptocurrencies, Koutmos, 2018; financial institutions, Diebold and Yilmaz, 2016). Recent studies have also documented the connectedness of economic uncertainties across countries (Antonakakis et al., 2018; Gabauer and Gupta 2018). However, studies that analyze the connectedness at different frequencies are very limited. The most recent studies in the area of frequency connectedness (Ferrer et al., 2018; Tiwari et al., 2018; and Wang and Wang, 2019) utilize the novel method of Barunik and Krehlik (2018).

Previous studies on the connectedness among assets in China are relatively limited. An essential contribution to the Chinese sectoral connectedness topic is study of Wang and Wang (2019). They investigate the frequency volatility spillovers between crude oil and Chinese sectoral equity markets and find that short-term spillovers are the main drivers of total volatility spillovers. In the similar line of research, Chan et al. (2016) provide an extensive analysis of links of Real Estate sector with other sectors in China, but they exclude the financial sectors and do not examine frequency connectedness. Some other recent studies include Wang et al. (2018b) who examine the volatility connectedness of the Chinese banking system, Wang et al. (2018a) who analyze the connectedness of the financial institutions in China, and Zhang and Fan (2019) who study the connectedness of China's urban housing prices.

This study complements previous studies on the connectedness at different frequencies and extends the literature as follows: We are the first to investigate the frequency connectedness of equity volatilities across different industries by applying a novel method of Barunik and Krehlik (2018, hereafter BK) and we also account for the potential breakpoints of the volatility connectedness by applying the Bai–Perron test (Bai and Perron 1998). Our focus is on the industries in China, since recent literature pointed out that certain Chinese industries such as Banking and manufacturing-related industries play important roles in the global financial and economic stability. Two most closely related studies are Wang and Wang (2019) and Chan et al. (2016). Our study differs from Wang and Wang (2019) in that we consider the connectedness among the Chinese sectoral equity markets, whereas Wang and Wang (2019) focus on the connectedness between crude oil prices and Chinese sectoral equity markets and do not analyze the connections among the various sectoral equity markets. Compared with the study of Chan et al. (2016) that excludes all the financial sectors, our study also includes the sector of Banks, which is an important sector from the perspective of risk connectedness/spillovers in an economy. After the Global Financial crisis, there was a shift of global systemically important banks from the developed economies to the emerging economies, particularly China (Alessandri et al., 2015). Hence, it is interesting to see whether the connectedness pattern for the Chinese banking sector changed after the shift in the global systemically important banks. Our study also differs from Chan et al. (2016) in that we focus on the equity volatility of the industries rather than the credit risk, and we distinguish the connectedness among the industries at different frequencies over different time periods. This distinction may be important, as our results show that the importance of an industry as a target or source of risks depends on the frequency and time period. In addition, by accounting for the breakpoints of volatility connectedness, our study enables identifying important subperiods (such as periods of subprime crisis and European debt crisis) in which volatility connectedness changes, shedding light on the underlying frequency sources of volatility connectedness and systemic risk during these subperiods.

2. Data and method

Our dataset includes the daily high, low, opening, and closing equity indexes of 12 industries in China (data is obtained from Datastream). Based on the industry classifications of listed firms by China Securities Regulatory Commission, there are 19 industries (the highest-level classifications). We select industries from the FTSE CHINA 600 industries in Datastream that match these 19 industries.[1] The 12 matched industries are Mining, Auto and Parts, Chemicals, Electricity, Construction and Materials, General Retailers, Industrial Transportation, Software and Computer Services, Banks, Real Estate, Health Care, and Media. The sample period of the study ranges from October 8, 2003 to April 30, 2018. In this study, we utilize the methodology of Garman and Klass (1980) to obtain daily range-based volatility estimate.[2] The volatility estimate is then transformed into log volatility.

For the method, we employ the frequency domain connectedness measure of BK which is built on the idea of Diebold and Yilmaz (2012; hereafter DY). DY construct the connectedness measures based on the generalized forecast error variance decompositions (GFEVD). Taking into account the heterogeneous frequency responses to economic shocks, BK extend the DY connectedness and develop connectedness measures based on the spectral representation of GFEVD. BK frequency connectedness decomposes the DY connectedness into separate parts that in sum give the original DY connectedness and reveal the frequency sources of the connectedness (For technical details, see Appendix). In the empirical analysis, we focus on the frequency bands up to 1 week (or 5 days),

[1] As Real Estate industry is not one of the 42 FTSE CHINA 600 industries in Datastream, we use the equity index of Shenzhen Real Estate to represent the Real Estate industry. Since there are many sub-industries for the industry of Manufacturing, two sub-industries are included to represent the industry of Manufacturing: Auto and Parts and Chemicals.

[2] Range-based volatility estimate for a given day is $\tilde{\sigma}^2 = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2$, where h, l, o, and c are the log daily high price, log daily low price, log opening price, and log closing price, respectively.

Fig. 1. Overall connectedness. The solid line is the DY connectedness; the solid gray line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

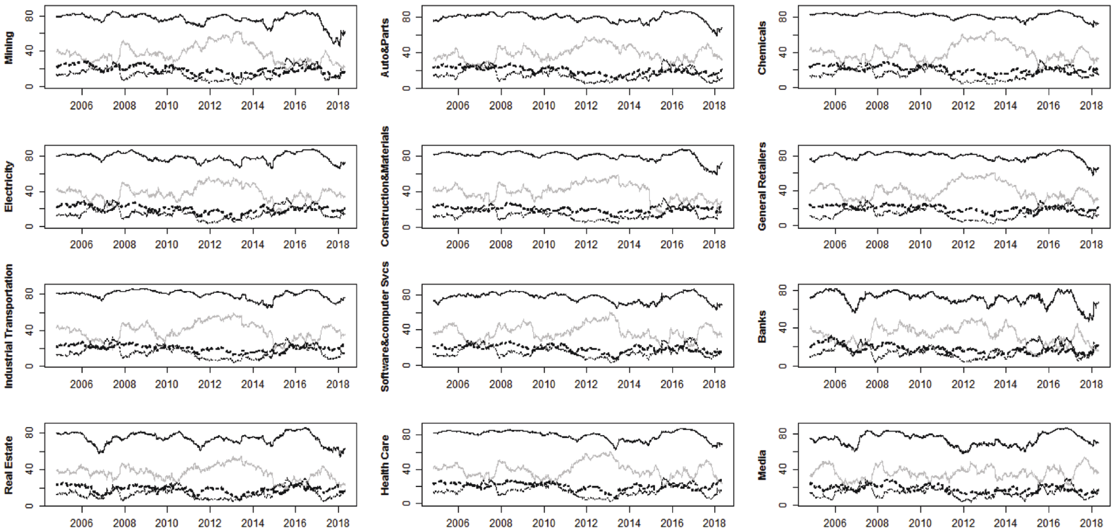

Fig. 2. FROM connectedness. Each of the above graphs shows the dynamic connectedness from all the other industries to a given industry: the solid line is the DY connectedness; the solid gray line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

1 week to 1 month (or 20 days), and 1 month to 1 year (or 250 days), which corresponds to our short-, medium-, and long-term frequency connectedness, respectively.

3. Results

Fig. 1 shows the overall DY and BK connectedness.[3] Among the four connectedness measures, short-term BK connectedness shows

[3] Volatilities of the selected industries appear to be stationary and have kurtosis value close to that of normal distribution (see Table A1 in the appendix for the descriptive statistics of the volatilities of the selected industries). We estimate the dynamic connectedness with a rolling window of 1 year (250 days) and set the vector auto-regression order to 3 and forecast horizon to 100 days. We obtain very similar trend for the overall DY and BK connectedness, when we change the vector auto-regression order to 2, 4, or 5, or the forecast horizon to 80 or 120 (results available upon request). For the static (full-sample) DY and BK connectedness, see Tables A2, A3, A4, and A5 in the appendix.

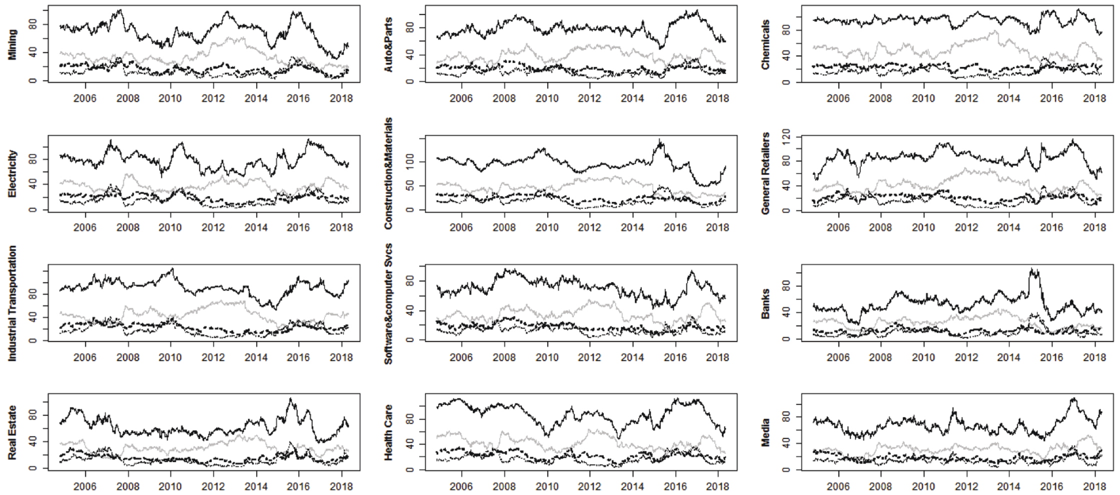

Fig. 3. TO connectedness. Each of the above graphs shows the dynamic connectedness from a given industry to all the other industries: the solid line is the DY connectedness; the solid gray line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

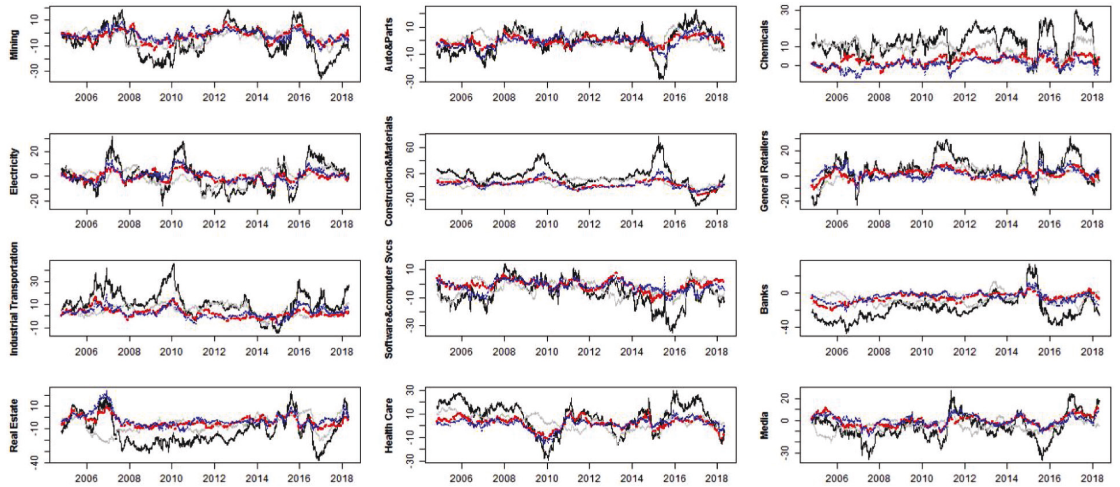

Fig. 4. Net total directional connectedness. Each of the above graphs shows the dynamic net total directional connectedness from a given industry to all the other industries: the solid line is the DY connectedness; the solid gray line is the short-term BK connectedness; the dashed red line is the medium-term BK connectedness; the dotted blue line is the long-term BK connectedness.

the largest fluctuations. Overall DY connectedness showed large decrease at the end of the sample period, which was caused by the initial decrease of long-term BK connectedness followed by the decrease of short-term BK connectedness. Short-term BK connectedness increased significantly from May 2010 to the end of 2011, resulting in the increase of overall DY connectedness during the European debt crisis. Thus, market participants in China appear to expect the shocks during the European debt crisis to have short-term impact.

Fig. 2 displays the connectedness FROM all the other industries to each of the industries. The FROM connectedness showed similar trend to the overall connectedness. Compared to the overall and FROM connectedness, connectedness from each of the industries TO all the other industries were more volatile during the sample period (see Fig. 3). Figs. 1–3 show that short-term BK connectedness is

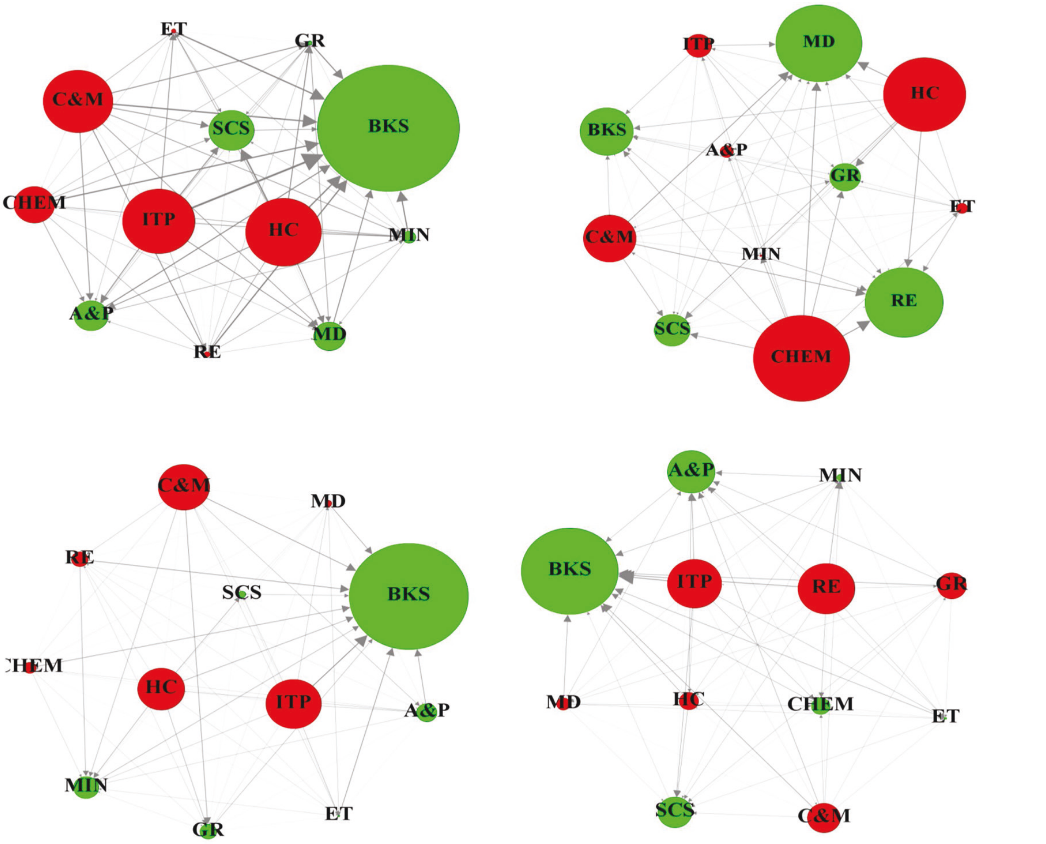

Fig. 5. Average net pairwise directional connectedness from 26.10.2004 to 18.4.2007. The upper left graph is the DY connectedness; the upper right graph is the short-term BK connectedness; the lower left graph is the medium-term BK connectedness; the lower right graph is the long-term BK connectedness. An arrow from A to B shows that the average net pairwise directional connectedness from industry A to industry B is positive, and larger arrows represent relatively larger connectedness. In each graph, the size of a circle represents the relative size of the average net directional connectedness from an industry to all the other industries: when the average net directional connectedness from an industry to all the other industries is positive (negative), it is shown in red (green). Abbreviations of the industry names: Mining = MIN, Auto and Parts = A&P, Chemicals = CHEM, Electricity = ET, Construction and Materials = C&M, General Retailers = GR, Industrial Transportation = ITP, Software and Computer Services = SCS, Banks = BKS, Real Estate = RE, Health Care = HC, and Media = MD.

generally larger than the medium- and long-term BK connectedness over the sample period. This result suggests the dominating role of short-term component for the frequency dependent connectedness measures, which is in line with the finding of Ferrer et al. (2018) and Wang and Wang (2019). Fig. 4 shows the difference between the TO connectedness and FROM connectedness (i.e., the net total directional connectedness). Over the sample period, Banking industry was mostly a net volatility receiver, and the industry of Construction and Materials and the industry of Industrial Transportation were mostly net volatility transmitters.

To account for the potential breakpoints of the volatility connectedness, we apply the Bai-Perron test to the overall DY connectedness. Bai-Perron test suggests four breakpoints or five sub-periods over the sample period: 26.10.2004–18.4.2007, 19.4.2007–25.1.2011, 26.1.2011–19.2.2013, 20.2.2013–7.4.2015, and 8.4.2015–30.4.2018. The second and the third sub-period may correspond to the Global Financial crisis and European debt crisis, respectively. For each sub-period, we calculate the average net pairwise directional connectedness among the industries and present the results in Figs. 5–9. Fig. 5 shows that for the aggregate DY and disaggregate medium- and long-term BK connectedness, Banking industry was the main receiver of volatility connectedness before the Global Financial crisis, with net pairwise connectedness coming from Industrial Transportation and Construction and Materials to Banking industry. In contrast, for the short-term BK connectedness arising from the short-term impact of shocks, Media and Real Estate industries were the main receivers of volatility connectedness.

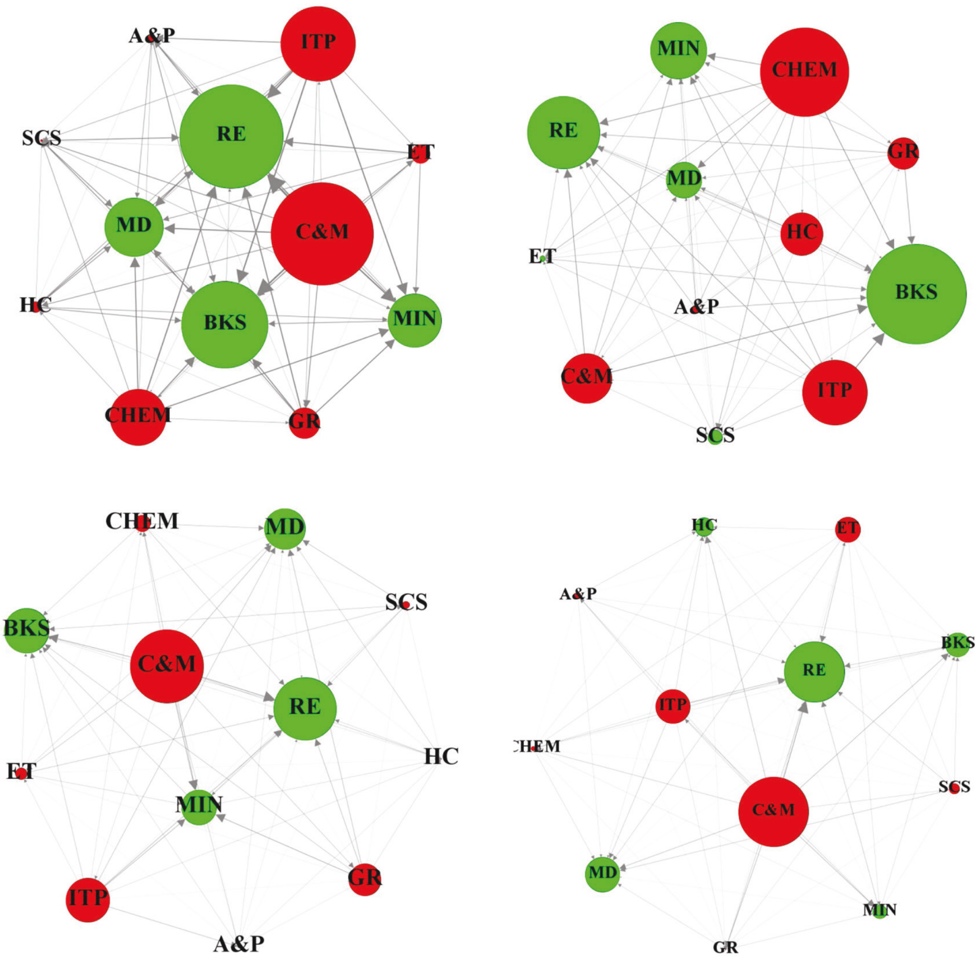

Fig. 6. Average net pairwise directional connectedness from 19.4.2007 to 25.1.2011. Notes: see Fig. 5.

Fig. 6 shows that for all the connectedness measures, during the Global Financial crisis, there was large volatility connectedness transmitted to the Banking industry and Real Estate industry, particularly from the industry of Construction and Materials and the industry of Industrial Transportation. In addition, there was also significant volatility connectedness from Chemicals to other industries in the short-run. These results are in line with the Baum et al. (2015) who demonstrate that the economic figures for manufacturing and industrial output are considered as the barometers of the state of the world economy. Analogously, during the European debt crisis, Banks and Real Estate were still the major receivers of volatility connectedness (see Fig. 7). However, the major sources of risks were different at different frequencies; for the shocks with short-term impact, the major sources of risks were the industries of Construction and Materials, Chemicals, and Industrial Transportation; for the shocks with medium-term impact, the major sources of risks were the industries of Chemicals and Health Care; for the shocks with long-term impact, the major source of risks was the Media industry.

During the fourth sub-period from 20.2.2013 to 7.4.2015, Construction and Materials and Chemicals were the main sources of volatility connectedness, while the main receivers of volatility connectedness were different at different levels of frequencies (see Fig. 8). For instance, Software and Computer services was the main receiver at short and medium term, while for long term Real Estate was the largest receiver. In contrast, during the last sub-period from 8.4.2015 to 30.4.2018, Banking industry was the main receiver of volatility connectedness, with different sources of risks at different levels of frequencies (see Fig. 9). More specifically, Chemicals was the main source of short and medium term volatility connectedness, while Industrial Transportation was the largest

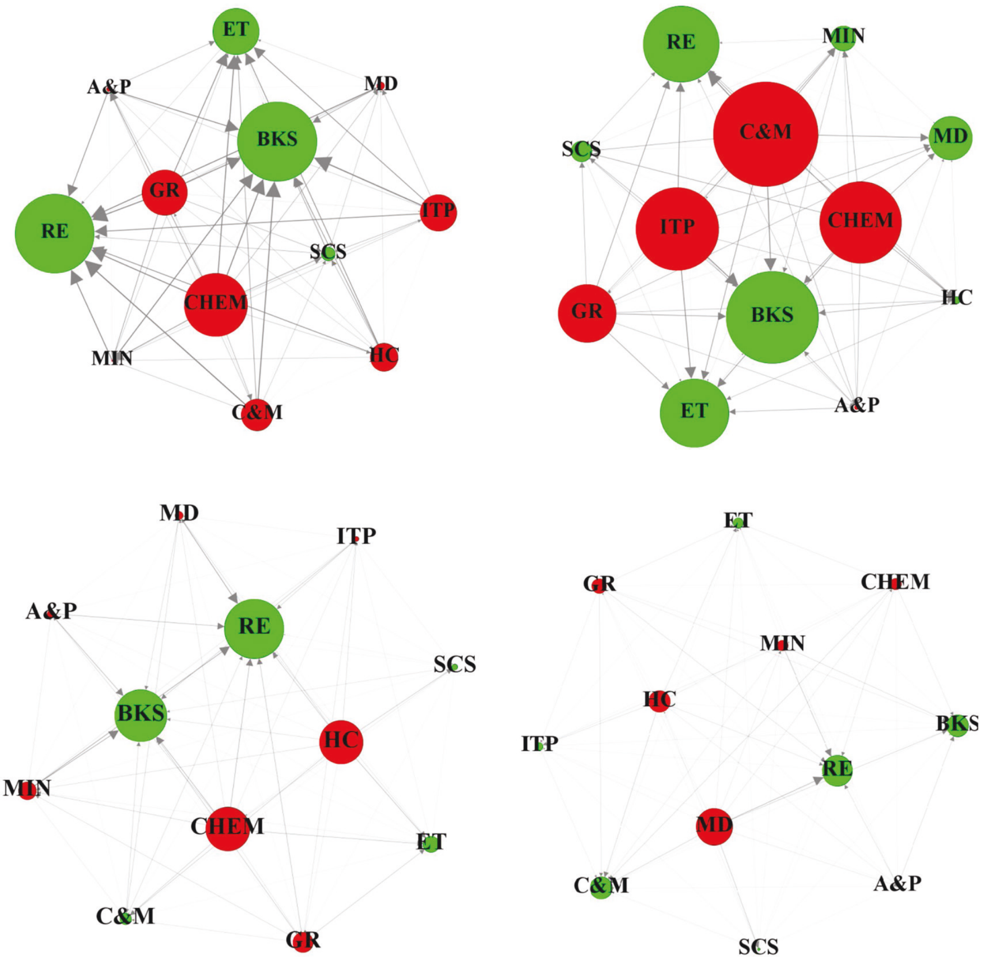

Fig. 7. Average net pairwise directional connectedness from 26.1.2011 to 19.2.2013. Notes: see Fig. 5.

source of long term volatility connectedness.

The above analysis indicates that the main targets of risks in China are Banking and Real Estate, while the main sources of risks are Construction and Materials, Industrial Transportation and Chemicals. These findings are consistent with those of Baum et al. (2015) and Chan et al. (2016). Studying the non-financial sectors, Chan et al. (2016) find that the Real Estate-Construction sector in China contributes significantly to the overall economic output, while Baum et al. (2015) show that figures related to Chinese manufacturing and industrial output are of particular importance. Overall, the results of the study provide interesting insight into which industries may be essential for maintaining financial stability over different time periods and at different frequency levels.

4. Conclusions

Recent research indicates that certain sectors of the Chinese economy have an increasingly important role in the world economy. In this light, we contribute to the literature by examining the volatility connectedness across different industries in China. For that purpose, we use the BK frequency connectedness method, which is advantageous for identifying sources and targets of risk within intersectoral framework. Specifically, it shows whether the volatility connectedness results from the short-, medium-, or long-term impact of shocks and thus reveals the underlying frequency sources of volatility connectedness. This is important, given that different

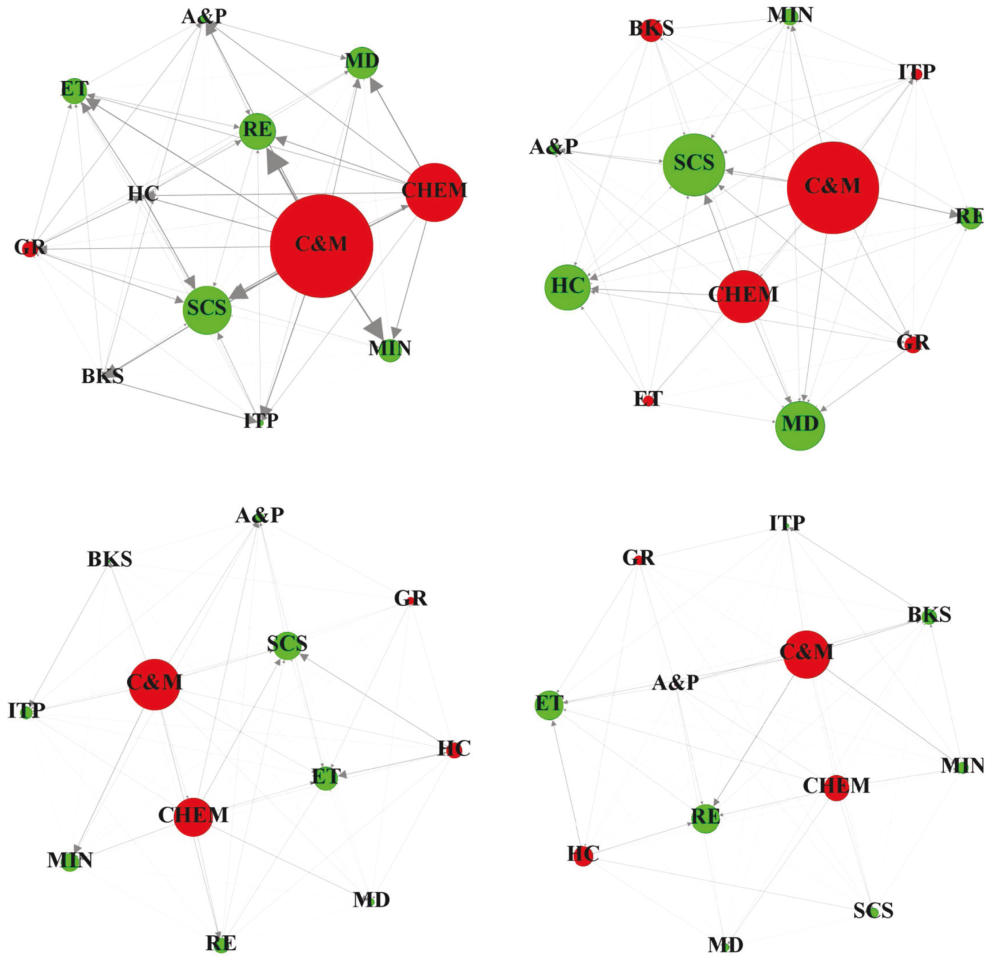

Fig. 8. Average net pairwise directional connectedness from 20.2.2013 to 7.4.2015. Notes: see Fig. 5.

agents may be interested in different level of connectedness: short-term investors may be interested in the high frequency pairwise connectedness between firms or industries, while policy makers may be concerned with the low frequency system-wide connectedness.

The results of our study show that before the Global Financial crisis, Banking industry in China was the major target of risks at medium and low frequencies, while Real Estate industry was a main target of risks at high frequency. Furthermore, during the periods of the Global Financial and European debt crisis, both the Banking industry and the Real Estate industry were the main target of risks at all the frequency levels, while the industry of Construction and Materials and the industry of Industrial Transportation were important sources of risks. Overall, the study highlights the importance of the use of frequency connectedness method such that the main targets and sources of risks at different frequencies over different time periods can be identified, providing essential information for the monitoring of the financial market.

In this study, we only consider an industry as a direct target or source of risks for the case of China. However, an industry as a direct target of risks in China may be a source of risks to other industries in other countries; similarly, an industry as a direct source of risks in China could also result from the risks of other industries in other countries. Therefore, future research could take into account these indirect effects and study the frequency connectedness of equity volatilities across different industries in different countries.

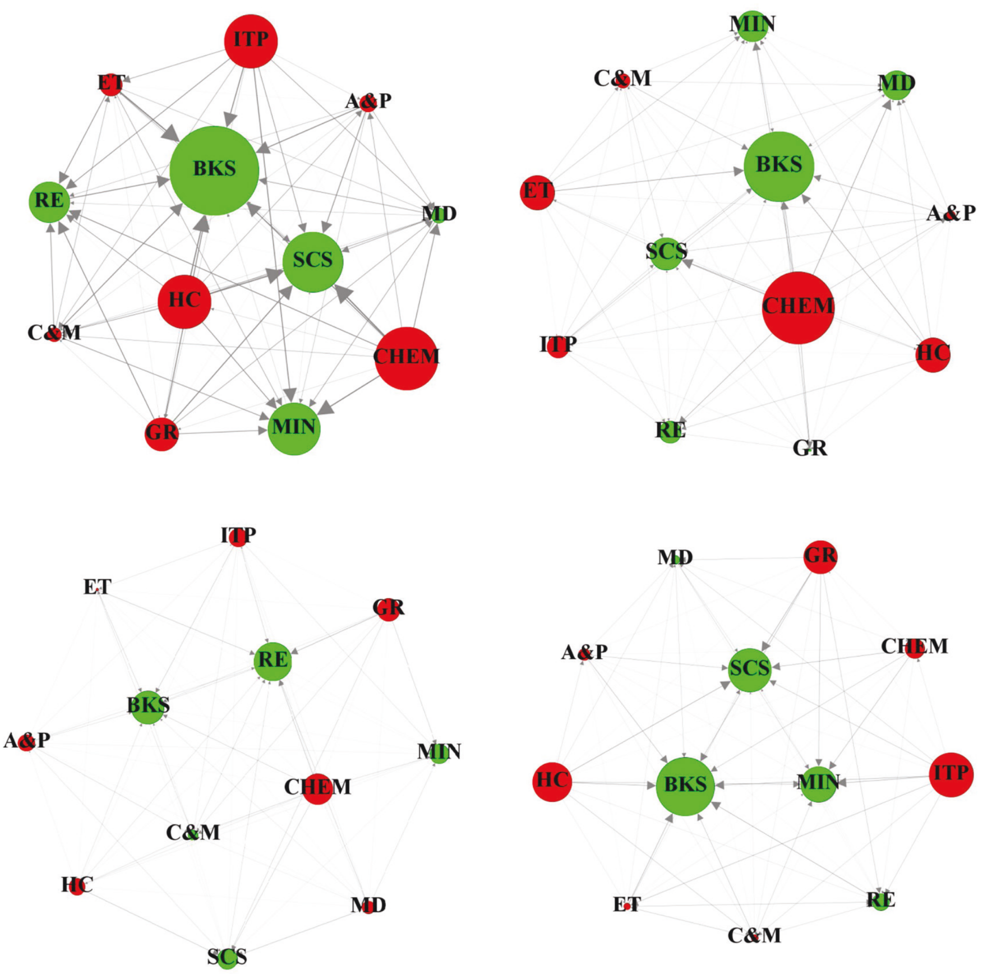

Fig. 9. Average net pairwise directional connectedness from 8.4.2015 to 30.4.2018. Notes: see Fig. 5.

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CRediT authorship contribution statement

Junhua Jiang: Writing - original draft, Writing - review & editing, Software, Formal analysis, Investigation, Data curation. **Vanja Piljak:** Writing - original draft, Writing - review & editing. **Aviral Kumar Tiwari:** Conceptualization, Methodology. **Janne Äijö:** Writing - original draft, Writing - review & editing, Supervision.

Appendix

The frequency domain connectedness of Barunik and Krehlik (2018) may be briefly presented as below: let us assume that a n-variate vector z_t follows a covariance-stationary VAR(p) process with the following moving average VMA(∞) representation

$$z_t = \Omega(L)\in_t \tag{1}$$

where Ω(L) and $\in_t$ respectively are $n \times n$infinite lag polynomial matrix of VMA coefficients, and white-noise term. Following Diebold and Yilmaz (2012), the generalized forecast error variance decomposition (GFEVD) may be presented as below:

Table A1
Descriptive statistics of the log volatilities of the selected industries.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD
Mean	−4.30	−4.43	−4.51	−4.67	−4.46	−4.48	−4.61	−4.28	−4.52	−4.33	−4.64	−4.33
Max.	−2.47	−2.51	−2.62	−2.55	−2.52	−2.26	−2.48	−2.24	−2.50	−2.53	−2.60	−2.38
Min.	−6.10	−6.46	−6.45	−6.61	−6.00	−6.23	−6.17	−6.42	−6.58	−6.51	−6.70	−6.49
Std. Dev.	0.55	0.57	0.54	0.60	0.55	0.55	0.58	0.52	0.63	0.57	0.58	0.60
Skewness	0.16	0.11	0.18	0.26	0.36	0.22	0.33	0.11	−0.06	0.00	0.12	−0.18
Kurtosis	2.87	2.97	3.06	3.01	3.07	3.09	2.90	3.02	2.83	2.95	3.18	2.91
Unit root	−5.84	−4.96	−6.36	−5.54	−5.13	−4.11	−6.34	−2.02	−4.95	−3.56	−3.37	−4.68

Notes: The last row shows the Dickey-Fuller GLS statistics for unit root test (Elliott et al., 1996). All the test statistics are statistically significant at the 1% significance level (except for SCS, which is statistically significant at the 5% significance level). Abbreviations of the industry names: Mining = MIN, Auto and Parts = A&P, Chemicals = CHEM, Electricity = ET, Construction and Materials = C&M, General Retailers = GR, Industrial Transportation = ITP, Software and Computer Services = SCS, Banks = BKS, Real Estate = RE, Health Care = HC, and Media = MD.

Table A2
Full-sample DY connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	19.89	7.41	9.04	7.87	8.70	7.51	9.03	4.77	6.06	7.06	7.23	5.43	80.11
A&P	7.00	17.32	8.93	8.44	7.36	7.79	8.75	5.51	5.76	6.81	8.96	7.38	82.68
CHEM	7.50	8.69	15.79	8.41	8.56	8.39	9.02	6.50	4.28	5.83	9.71	7.32	84.21
ET	6.42	7.92	7.79	18.64	8.90	7.40	10.43	4.79	6.20	5.98	8.10	7.42	81.36
C&M	7.20	7.34	8.65	9.04	17.79	7.78	10.45	5.32	5.23	7.16	8.15	5.88	82.21
GR	6.32	7.75	8.51	7.68	8.04	18.01	9.28	6.36	4.86	6.38	9.15	7.66	81.99
ITP	6.89	7.70	8.06	9.49	9.32	8.24	18.39	5.06	6.49	5.87	7.57	6.90	81.61
SCS	5.69	7.40	8.86	7.03	7.12	8.52	7.63	19.77	4.36	5.11	9.17	9.33	80.23
BKS	7.05	7.56	5.70	8.21	6.74	6.17	8.98	4.10	24.21	8.57	6.15	6.56	75.79
RE	7.30	7.59	6.76	7.39	8.40	7.42	7.64	4.43	7.30	21.70	7.25	6.82	78.30
HC	6.10	8.85	9.66	8.40	7.75	8.93	8.45	6.21	4.87	6.29	17.08	7.40	82.92
MD	4.90	7.81	7.56	8.14	5.81	8.15	8.09	7.47	4.96	6.27	7.86	22.96	77.04
TO	72.38	86.02	89.52	90.09	86.71	86.31	97.73	60.53	60.37	71.36	89.31	78.11	**80.70**

Notes: The upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

Table A3
Full-sample short-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	7.99	2.02	2.76	2.06	2.40	2.00	2.33	1.35	1.39	1.44	1.70	1.31	20.77
A&P	1.67	6.99	2.77	2.01	2.22	2.01	2.25	1.59	1.20	1.45	2.33	1.46	20.96
CHEM	2.24	2.59	6.46	2.26	2.74	2.45	2.64	2.13	1.16	1.60	2.80	1.85	24.46
ET	1.68	1.90	2.32	6.33	2.22	1.81	2.44	1.30	1.17	1.24	2.03	1.25	19.35
C&M	2.12	2.24	2.98	2.40	6.85	2.40	2.79	1.77	1.45	2.07	2.40	1.55	24.16
GR	1.85	2.11	2.79	2.03	2.48	7.20	2.39	2.09	1.17	1.61	2.74	1.79	23.04
ITP	1.85	2.07	2.62	2.39	2.52	2.08	6.13	1.47	1.38	1.42	2.06	1.37	21.22
SCS	1.53	2.14	3.06	1.82	2.34	2.65	2.14	9.48	0.90	1.56	2.78	2.89	23.82
BKS	1.48	1.49	1.51	1.54	1.74	1.36	1.87	0.83	8.33	1.48	1.41	0.83	15.53
RE	1.45	1.70	1.99	1.51	2.38	1.77	1.79	1.33	1.41	7.97	1.66	1.20	18.18
HC	1.45	2.29	2.96	2.11	2.35	2.57	2.18	2.12	1.12	1.41	6.75	1.75	22.31
MD	1.32	1.70	2.31	1.53	1.80	1.97	1.73	2.50	0.80	1.22	2.03	7.60	18.90
TO	18.64	22.24	28.06	21.65	25.20	23.07	24.55	18.47	13.14	16.48	23.93	17.26	**21.06**

Notes: The upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}((\Omega_h\Sigma)_{j,k})^2}{\sum_{h=0}^{H}(\Omega_h\Sigma\Omega')_{j,j}} \tag{2}$$

where $\sigma_{kk} = (\Sigma)_{k,k}$ (where Σ is the covariance matrix of white noise error terms) and Ω_h is a$n \times n$ matrix of VMA coefficients

Table A4
Full-sample medium-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	4.65	1.51	2.14	1.65	2.06	1.65	1.93	1.10	1.21	1.49	1.65	0.99	17.36
A&P	1.55	3.69	2.04	1.73	1.62	1.64	1.78	1.26	1.06	1.30	2.05	1.43	17.46
CHEM	1.70	1.89	3.73	1.82	1.99	1.87	1.89	1.57	0.75	1.11	2.32	1.50	18.40
ET	1.32	1.59	1.69	4.11	2.06	1.48	2.13	1.02	1.15	1.05	1.75	1.38	16.60
C&M	1.64	1.56	2.01	2.03	4.33	1.68	2.32	1.24	1.00	1.54	1.89	1.15	18.07
GR	1.34	1.66	1.98	1.57	1.86	4.16	1.97	1.52	0.86	1.26	2.14	1.56	17.72
ITP	1.51	1.58	1.77	1.98	2.20	1.77	4.08	1.11	1.26	1.06	1.64	1.30	17.18
SCS	1.28	1.56	2.09	1.47	1.64	1.92	1.57	4.76	0.84	0.88	2.22	1.97	17.45
BKS	1.33	1.34	1.07	1.46	1.33	1.06	1.64	0.82	5.16	1.51	1.10	1.02	13.68
RE	1.55	1.47	1.40	1.41	1.86	1.53	1.40	0.90	1.35	4.67	1.54	1.22	15.64
HC	1.34	1.95	2.32	1.76	1.77	1.96	1.77	1.38	0.86	1.23	3.94	1.42	17.76
MD	0.86	1.48	1.61	1.53	1.13	1.60	1.48	1.66	0.72	1.01	1.64	4.90	14.72
TO	15.43	17.58	20.12	18.40	19.52	18.17	19.86	13.58	11.06	13.44	19.95	14.93	**16.84**

Notes: The upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

Table A5
Full-sample long-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	5.05	2.57	2.84	2.74	2.90	2.58	3.17	1.57	2.24	2.71	2.61	1.99	27.90
A&P	2.50	4.46	2.79	3.07	2.35	2.73	3.08	1.78	2.22	2.61	3.06	2.88	29.07
CHEM	2.41	2.82	3.92	2.88	2.62	2.74	2.98	1.92	1.50	2.02	3.14	2.59	27.61
ET	2.24	2.89	2.53	5.51	3.12	2.68	3.86	1.63	2.47	2.34	2.87	3.06	29.67
C&M	2.33	2.36	2.51	3.09	4.65	2.48	3.61	1.57	1.79	2.34	2.62	2.05	26.76
GR	2.08	2.62	2.55	2.68	2.50	4.57	3.27	1.87	1.79	2.26	2.89	2.79	27.31
ITP	2.34	2.65	2.47	3.37	3.13	2.91	5.54	1.66	2.47	2.16	2.57	2.71	28.44
SCS	1.92	2.45	2.55	2.46	2.13	2.65	2.58	3.93	1.68	1.70	2.84	2.93	25.88
BKS	2.74	3.00	2.00	3.31	2.38	2.36	3.49	1.58	7.13	3.54	2.31	2.92	29.64
RE	2.84	2.86	2.22	2.86	2.77	2.68	2.85	1.43	2.90	6.07	2.66	2.77	28.84
HC	2.20	3.06	3.00	2.98	2.45	2.94	2.96	1.83	1.82	2.36	4.40	2.73	28.33
MD	1.71	2.97	2.39	3.25	1.85	2.97	3.12	2.20	2.11	2.52	2.73	6.93	27.83
TO	25.29	30.25	27.86	32.68	28.19	29.72	34.97	19.04	22.99	26.57	30.31	29.40	**28.10**

Notes: The upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

matching to lag h. The H-step ahead GFEVD of variable j due to shocks in variable k is represented by $(\theta_H)_{j,k}$. Following Barunik and Krehlik (2018), the frequency domain representation of Eq. (2) may be presented as follows:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1} |(\Omega(e^{-iw})\,\Sigma)_{j,k}|^{2}}{(\Omega(e^{-iw})\,\Sigma\Omega'(e^{+iw}))_{j,j}} \tag{3}$$

where $\Omega(e^{-iw}) = \sum_h e^{-iwh}\,\Omega_h$ presents a frequency response function using Fourier transform of Ω_h over generalized causation spectrum of frequencies $\omega = \in(-\pi, \pi)$. Further,$(f(\omega))_{j,k}$ presents the percentage of the spectrum of variable j at frequency ω due to shocks in variable k which may be interpreted as a within frequency causation (Barunik and Krehlik 2018). Assuming a frequency band $g = (c, d)$: $c, d \in (-\pi, \pi)$, $c < d$, the GFEVD on g is then defined as

$$(\theta_g)_{j,k} = \frac{1}{2\pi}\int_g \Gamma_j(\omega)\,(f(\omega))_{j,k} g\omega \tag{4}$$

where $\Gamma_j(\omega)$ represents the weighting function which is presented as follows:

$$\Gamma_j(\omega) = \frac{(\Omega(e^{-iw})\,\Sigma\Omega'(e^{+iw}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Omega(e^{-i\lambda})\,\Sigma\Omega'(e^{+i\lambda}))_{j,j} g\lambda} \tag{5}$$

which is the power of variable j at a given frequency and sums through frequencies to 2π. Following Barunik and Krehlik (2018), the normalized GFEVD on the frequency band g may be writtes as follows:

$$(\tilde{\theta}_g)_{j,k} = \frac{(\theta_g)_{j,k}}{\sum_k (\theta_\infty)_{j,k}} \tag{6}$$

where $(\theta_\infty)_{j,k}$ is the value of $(\theta_g)_{j,k}$ in Eq. (4) when the frequency band is $(-\pi, \pi)$. Therefore, the frequency domain connectedness on the frequency band g may be presented as follows:

$$C_g^F = 100\left(\frac{\sum^{(\tilde{\theta}_g)_{j,k}}}{\sum^{(\tilde{\theta}_\infty)_{j,k}}} - \frac{\sum_{j=k}(\tilde{\theta}_g)_{j,k}}{\sum^{(\tilde{\theta}_\infty)_{j,k}}}\right) \tag{7}$$

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Can Real Estate Regulatory Policies Constrain Real Estate Risks to Banks? Evidence from China

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Abstract

This study investigates the effects of real estate regulatory policies on the real estate risks to banks in China. The study shows that real estate control policies issued by the policy makers in China cannot constrain the risks of the real estate market to banks. Real estate stimulating policies, however, could raise the risks of the real estate market to banks, which mainly results from the effects of tax-related stimulating policies. The study also shows that real estate control policies affect the discount rate risks of the real estate firms to banks, while both the real estate control policies and the real estate stimulating policies show some effects on the overall risks of the real estate firms to banks.

Keywords: Real estate regulation; policy effect; Real estate risks; Banks; Return connectedness

JEL classifications: G21, L52, R38

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1. Introduction

Real constant quality house prices in the major cities of China have more than doubled during the first decade of this century (Wu et al. 2012).[1] In particular, following Chinese government's monetary stimulus program after the global financial crisis in 2008, state-owned banks dramatically increased their lending to centrally-controlled state-owned enterprises (CSOEs), and with the abundant funding from the state-owned banks, these CSOEs bid aggressively in residential land sales, contributing to the surge in real estate prices (Deng et al. 2015). Concerned with the rapid real estate price growth, policy makers in China issued a series of regulatory policies aimed at cooling the overheating real estate market.

In this study, we investigate whether the real estate regulatory policies issued by the Chinese policy makers played a role in constraining the real estate risks to banks in China. Specifically, by the framework of Campbell (1991), we first decompose the equity returns of the Chinese real estate firms into a discount rate news component and a cash flow news component, which reflect changes in expectation of future discount rates and changes in expectation of future dividends, respectively. Then, by the connectedness measure of Diebold and Yilmaz (2014), we study the overall return connectedness from the real estate firms to banks, the connectedness of the discount rate news component of the real estate firms to banks, and the connectedness of the cash flow news component of the real estate firms to banks. We argue that the overall return connectedness, the discount rate (news component) connectedness, and the cash flow (news component) connectedness of the real estate firms to banks reflect the overall risks of the real estate firms to banks, the discount rate risks of the real estate firms to banks, and the risks of the

[1] Based on the real estate transaction data in 24 large cities (see footnote 10), overall real estate prices in China over a more recent period from January 2010 to October 2017 increased by 58%.

real estate market to banks, respectively (see section 5.2). Finally, we examine the effects of real estate regulatory policies on these three types of real estate risks to banks.

Previous studies have investigated the impact of regulatory policies on the real estate market (e.g., Sun et al. 2017, Yu et al. 2017), focusing on the effects of regulatory policies on constraining real estate prices (e.g., Cocconcelli and Medda 2013, Kuttner and Shim 2013, Yu 2010, Crowe et al. 2013, Vandenbussche et al. 2015, Xu and Chen 2012). However, the issue of whether regulatory policies can constrain real estate risks, particularly real estate risks to banking sector, has been neglected, and this study fulfills the gap. Previous research suggests that it is difficult to determine whether a real estate price is too high or whether a real estate price bubble exists (Ahuja et al. 2010, Cadil 2009). Previous research also reveals the difficulty in distinguishing a good real estate price boom from a bad real estate price boom: good real estate price booms are benign and thus policy actions could restrict credit unnecessarily, while bad real estate price booms represent real estate bubbles and thus policy actions are needed (Crowe et al. 2013). Regulatory policies that constrain good real estate price booms could unwisely limit economic growth. Since high real estate risks are always bad[2], it could be more desirable to study the real estate risks, rather than the real estate price, and to examine the effects of regulatory policies on constraining the real estate risks.

This study could also have important policy implications. Firstly, the study analyzes the real estate risks to banks, which are closely monitored by the policy makers. As highlighted by the subprime mortgage crisis in 2008, real estate market plays an important role in financial stability and the real economy. The boom and bust cycles in real estate market contribute significantly to

[2] Just as investors would prefer low risks (and high returns), policy makers and bankers would prefer low real estate risks. Hence, for policy makers and bankers, high real estate risks may always be bad.

banking crises (Allen and Carletti 2013). Secondly, dividing the real estate regulatory policies into different types (financial policies, tax policies, land policies, and industrial policies) and investigating the effect of each type of policies, the study provides evidence on which type of real estate regulatory policies would be more effective in reducing the real estate risks to banks. Thirdly, after the global financial crisis, there was a shift of global systemically important banks from the developed economies to the emerging economies, particularly China (Alessandri et al. 2015). Therefore, given the gradually increasing role of the Chinese economy in the world economy, the potential real estate risks to banks in China have great implications for the global financial stability and economic growth.

The remainder of the study proceeds as follows. Section 2 reviews the literature. Section 3 provides an overview of the real estate regulatory policies in China. Section 4 describes the data. Section 5 presents the method. Section 6 shows the empirical results and Section 7 concludes the study.

2. Literature review

Rapid house price growth in the past decade has attracted numerous studies on the existence of potential real estate bubbles in China. For instance, Ahuja et al. (2010) find that except for some large cities which show excessive price growth, as of mid-2010 the overall real estate prices in China appear to be in line with the underlying market fundamentals. Feng and Wu (2015) also do not find evidence of house price bubbles at the national level in China. However, they suggest that the conclusion could be sensitive to the expected income growth rate. Ren et al. (2012) conclude that there are no rational expectation bubbles in the Chinese housing market over the period 1999-2009. Using data from 1998 to 2010, Dreger and Zhang (2013) find some evidence of housing price bubbles in China, particularly in the south-east coastal areas and special economic zones.

One of the concerns about the potential real estate bubble is the risks it may pose to the banking industry. Allen et al. (1995) show that bank returns are positively related to the real estate returns, and this relation is positively related to the bank's real estate exposure. Mei and Saunders (1995) show that real estate market conditions affect the (ex ante) risk premiums on bank stocks, and the time-varying risk premiums reflect the changes in bank real estate lending. The study by Martins et al. (2016) suggests that real estate factor is a priced factor for the bank stock returns in 15 European countries. Koetter and Poghosyan (2010) conclude that deviations of real estate price from its fundamental value, rather than the real estate price level itself, contribute to bank instability. Focusing on the regional commercial banks in China, Zhang et al. (2016) find that lower growth rate of real estate investment increases bank instability, and this relation between real estate investment and bank instability is affected by real estate market cycles and the competition level of the regional banks. Li et al. (2016) analyze the full-sample static effect of the systemic risk in the real estate sector on banking return in China and show that higher systemic risk in the real estate sector leads to lower banking return. Jiang and Äijö (2018) study the volatility connectedness across China's real estate firms and financial institutions and find that connectedness from real estate firms to banks decreased over the studied period.

To limit real estate market risk, policy makers have applied various policy measures. Vandenbussche et al. (2015) reveal that some macroprudential policies adopted by countries in Central, Eastern, and Southeastern Europe were effective in curbing housing price inflation. Cocconcelli and Medda (2013) study the Estonian real estate market and find that rigorously implemented land tax policy can reduce the effects of real estate boom-bust cycle. Crowe et al.

(2013) highlight the crucial role of macroprudential measures and the importance of complementing these measures with monetary policy in dealing with real estate booms. Goukasian and Majbouri (2010) show the strong impact of US monetary policy on the stock returns of real estate-related industries. Analyzing the effectiveness of nine non-interest rate policies in 57 economies, Kuttner and Shim (2013) find that only increases in housing-related taxes have significant effect on house prices.

Wang and Sun (2013) maintain that required reserve ratio and house-related policies in China can help to constrain excessive house price growth. Wei et al. (2014) document that rising interest rate or expansion of bank credit stimulates real estate investment in China, and the investment in eastern coastal regions is more responsive to bank credit supply than other regions. Yu et al. (2017) show that regulatory policies in China influence the investment expenditures of real estate enterprises, particularly for the non-state-owned real estate enterprises limited by financing constraints. Xu and Chen (2012) demonstrate the significant impact of Chinese monetary policy on real estate price growth. The analysis of Zhang (2008) suggests the efficacy of land supply policy on the real estate market in China. Yu (2010) finds that variables controlled by real estate policy affect house price in China. The studies by Li et al. (2017) and Sun et al. (2017) show the profound influence of home purchase restrictions policy on China's real estate market.

Despite the numerous studies on the existence of potential real estate bubbles in China, the risks real estate bubbles may pose to the banking industry, and the impact of various policy measures on real estate market, the issue of whether policy measures can constrain real estate risks to banking sector has been neglected. In this study, we analyze the effects of real estate regulatory policies on the real estate risks to banks in the case of China. Over different time periods, the objective of real estate regulatory policies by the Chinese policy makers was different: during a controlling period, the objective is to stabilize or slow the housing price growth; during a stimulating period, the objective is to support or stimulate the real estate market. We define a regulatory policy issued during a controlling period as a controlling policy and a regulatory policy issued during a stimulating period as a stimulating policy. Over a given time period (either a controlling or a stimulating period), policy issuers in China may issue various types of real estate regulatory policies (such as financial policies, tax policies, land policies, or industrial policies), which regulate various aspects of the real estate industry (see section 3 and table 1 in the appendix).

3. Real estate regulatory policies in China

Since the reform of the real estate market during the late 1990s, policy makers in China have carried out several rounds of real estate regulations. A recent report by Ren (2017) divides China's real estate regulatory policies after the real estate market reform into six rounds. Based on Ren's division, the first round of regulations from 2002 to 2004 focused on slowing the gradually overheating real estate market. Although this round of regulations reduced real estate investment, it did not accomplish the goal of slowing real estate price growth. The second round of regulations from 2005 to 2007 further emphasized stabilizing the real estate prices. This round of regulations also did not have the intended effect, and rapid house price growth continued. The year 2008 was a turning point, with housing sales and housing prices starting to decrease. However, the occurrence of global financial crisis in 2008 shifted the objective of macro-regulations to avoiding potential dip in economic growth. Hence, the third round of regulations from 2008 to 2009 concentrated on stimulating the real estate market. This round of regulations resulted in a surge in both real estate sales and real estate prices.

Following the unprecedented price growth, the government initiated the fourth round of regulations from 2010 to 2013, commonly observed to be the most stringent round of real estate regulations. The growth of real estate prices slowed down after this round of regulations. The fifth round of regulations from 2014 to September 2016 sought to reduce housing inventories. During this period, housing prices in the first and second tier large cities increased significantly, while prices in the third and fourth tier relatively smaller cities were more or less stable. The sixth round of regulations from September 2016 to 2017 highlighted the combination of short-term regulatory policies and long-term regulatory mechanisms. This round of regulations showed some effect of controlling real estate price growth.

The characteristics of these six rounds of regulations indicate that the sample period can be separated into two types of sub-periods: controlling periods and stimulating periods. During a controlling period, the goal of real estate regulatory policies is to stabilize the housing prices or slow the housing price growth. The goal of real estate regulatory policies during a stimulating period is to support or stimulate the real estate market. The report by Ren (2017) suggests that there were three controlling periods (2005-Jul. 2008, Dec. 2009-May 2014, and Oct. 2016-2017) and two stimulating periods (Aug. 2008-Nov. 2009 and Jun. 2014-Sep. 2016) from 2005 to 2017 (see table 1 in the appendix). We refer to a regulatory policy issued during a controlling (stimulating) period as a controlling (stimulating) policy.

Table 1 in the appendix shows the major real estate regulatory policies in China from 2005 to 2017, which is compiled from three studies by China Index Academy (2017), He (2016, 107–112), and Ren (2017). Since monetary policies commonly aim at regulating the overall macro-economy, we consider only the regulatory policies targeted specifically at the real estate markets and exclude the monetary policies. As in He (2016), we divide the real estate regulatory policies into four categories. The first category of policies is the financial policies mainly regulating the supply of real estate loans by banks. The second category of policies is the tax policies stipulating the tax issues related to housing transactions. Another category of policies is the land policies regulating the land supply, acquisition, usage, etc. The last category of policies is the industrial policies consisting of all the policies targeted at the real estate industry but not included in the other three categories. It should be noted that some regulatory policies might belong to multiple categories, because policy makers in China sometimes issue comprehensive policies to regulate the real estate market from different aspects. We determine the type of a policy based on the main features of the policy described by the three previous studies (see Table 1 in the appendix).

4. Data

All the equity-related data included in this study were downloaded from Thomson Reuters Datastream. To represent the sector of real estate firms and the sector of banks in China, we use China A-Datastream Real Estate index and China A-Datastream Banks index, respectively.[3] We include the total return index for these two indexes and the dividend yield for the China A-Datastream Real Estate index. To construct the variable of small-stock value spread, we select the total return index of small growth stocks and that of small value stocks in China (MSCI index). 3-month and 10-year government bond yield were retrieved from the website of China Bond.[4] To control for the impact of the other firms in the Chinese stock market, we compute the value-weighted returns on a portfolio of "other firms", which consists of companies that are constituent of the SSE 50 index, excluding all the real estate firms and banks (as of November 2,

[3] The constituents of the two equity indexes, China A-Datastream Real Estate index and China A-Datastream Banks index, consist of 19 real estate firms and 26 banks, respectively, which include the largest real estate firms and banks in China.
[4] www.chinabond.com.cn

2017).[5] The data of the study are time series data, and the sample period of the study ranges from January 2002 to October 2017.

5. Method

To analyze the risks of the estate market and real estate firms to banks, we first decompose the total unexpected excess returns of the real estate firms into a component due to news about expected future discount rates and a component due to news about expected future cash flows. We then compute the overall return connectedness, discount rate component connectedness, and cash flow component connectedness of the real estate firms to banks. Finally, we examine the effects of real estate regulatory policies on the return and return component connectedness of the real estate firms to banks.

5.1. Return decomposition

Utilizing the log-linear return approximation of Campbell and Shiller (1988), Campbell (1991) presents the following decomposition of unexpected excess returns:[6]

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\Sigma_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\Sigma_{j=1}^{\infty}\rho^j r_{t+1+j} \equiv N_{CF,t+1} - N_{DR,t+1}, \quad (1)$$

where r_{t+1} is the log excess return from time t to time t+1, E_t is the expectation conditional on the information at time t, ρ is a constant smaller than one, d_t is the log dividend, Δ denotes the one period difference, $N_{CF,t+1}$ represents the cash flow component of the unexpected return, and $N_{DR,t+1}$ denotes the discount rate component of the unexpected return.

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[5] The portfolio of other firms contains 35 stocks. We compute the daily value-weighted returns on the portfolio of these 35 stocks and aggregate the daily returns to obtain the monthly returns. According to Shanghai Stock Exchange, SSE 50 index includes 50 representative stocks that are large, liquid in the Shanghai stock market.

[6] In a more strict sense, the relationship in Eq. (1) holds only for unexpected real returns. When real interest rates are constant, Eq. (1) also holds for unexpected excess returns (see the appendix to Campbell and Vuolteenaho, 2004). As in Campbell and Vuolteenaho (2004), we use excess returns instead of real returns.

Let z_{t+1} be a k-by-1 vector whose first element is r_{t+1} and assume z_{t+1} follows the following VAR(1) model:

$$z_{t+1} = c + Az_t + u_{t+1}, \qquad (2)$$

where c is a k-by-1 vector of parameters, A is a k-by-k matrix of parameters, and u_{t+1} is a k-by-1 vector of errors. Then, Eqs. (1) and (2) can be used to show that

$$N_{DR,t+1} = e1'\rho A(I - \rho A)^{-1}u_{t+1}, \qquad (3)$$

$$N_{CF,t+1} = [e1' + e1'\rho A(I - \rho A)^{-1}]u_{t+1}, \qquad (4)$$

where $e1$ is a k-by-1 vector, whose first element is one and zeros elsewhere; I is a k-by-k identity matrix.

Following Campbell and Vuolteenaho (2004) and Engsted et al. (2012), we include the following four variables in the state vector z_{t+1}: log excess return of the real estate firms (monthly log return in excess of the 3-month government bond rate), log dividend yield of the real estate firms, term spread (the difference between 10-year government bond yield and 3-month government bond yield), and small-stock value spread.[7] Due to data availability, we construct the small-stock value spread as the difference between the cumulative returns of the small growth stocks and small value stocks in the previous year (proxied by the return difference between MSCI China small growth stocks and MSCI China small value stocks in the previous year).

[7] Previous studies suggest that return decompositions could be sensitive to the predictive variables included in the state vector. To alleviate this problem, we follow the recommendations of Engsted et al. (2012) and include the "theoretically correct" variable, dividend-yield, as one of the predictive variables. Moreover, as a robustness check, we also include two additional predictive variables in the state vector: 3-month government bond rate and stock variance of the real estate firms (see Campbell and Vuolteenaho, 2004; Guo, 2006). Stock variance of the real estate firms for a given month is the realized variance over the month calculated based on the daily returns on the China A-Datastream Real Estate index. The results from the robustness check (available upon request) provide very similar trend of discount rate and cash flow connectedness of the real estate firms to banks.

Eleswarapu and Reinganum (2004) provide evidence that return differences between growth stocks and value stocks in the prior 36 months can predict stock market returns. To construct a comparable measure of small-stock value spread to that of Campbell and Vuolteenaho (2004), we use cumulative returns in the previous year, instead of the prior 36 months. As in Campbell and Vuolteenaho (2004), we set the constant ρ to $0.95^{1/12}$ in this study.

5.2. Return connectedness

The study analyzes the overall return connectedness, discount rate connectedness, and cash flow connectedness of the real estate firms to banks by the method of Diebold and Yilmaz (2014). Based on the forecast error variance decompositions, Diebold and Yilmaz (2014) define the pairwise directional connectedness between any two variables in the system. In this study, we only consider the pairwise directional connectedness from the real estate firms to banks.

To control for the impact of the other companies in the Chinese stock market, we also include the returns of companies that are constituent of the SSE 50 index, excluding all the real estate firms and banks (as of November 2, 2017). Therefore, to obtain the forecast error variance decompositions, our vector for the vector auto-regression contains three variables: one variable is either the overall (excess) returns, the discount rate news component, or the cash flow news component of the real estate firms; the other two variables are the returns of the banks and the returns of the other companies. We use parsimonious VAR(1) models and compute the dynamic connectedness based on forecast error variance decompositions with a rolling window of 36 months and a forecast horizon of 6 months.[8]

[8] For the majority of the rolling windows, the optimal lag order selected by AIC is one (with the maximum lag order set to four). We obtain similar trends for all the dynamic connectedness when we change the rolling window length to 48 months or the forecast horizon to 3 months (the results are available upon request).

We argue that connectedness from the real estate firms to banks provides intuitive ways to measure the risk contribution of the real estate market or real estate firms to banks. The connectedness measures are based on the forecast error variance decompositions that show the fractions of uncertainty (forecast error variance) in a variable due to shocks in other variables in the system. For example, cash flow connectedness of the real estate firms to banks shows the fraction of uncertainty in banks' returns due to shocks in the cash flow news component of the real estate firms. The cash flow news component of the real estate firms is closely associated with the changes in expected real estate prices, since the expected cash flows (or dividends) of real estate firms are closely related to the expected real estate prices. Hence, the cash flow connectedness of the real estate firms to banks reflects the fraction of uncertainty in banks' returns due to shocks in expected real estate prices, or the risks of expected real estate prices changes to banks.[9] Analogously, the overall return connectedness from the real estate firms to banks reflects the overall risks of the real estate firms to banks, and the discount rate connectedness of the real estate firms to banks reflects the discount rate risks of the real estate firms to banks.

One may notice that the discount rates are the rates that are used to discount the cash flows of real estate firms, in order to obtain the value of these firms. The discount rates are the sum of two parts: risk-free rate and risk premium. The rates of banks loans to real estate firms may be affected by both the risk-free rate and risk premium. In addition, the rates of banks loans to real estate firms are linked to the profitability of banks, which in turn affects the equity returns on banks. Thus, the discount rates of real estate firms could be indirectly linked to the equity returns on banks, and the discount rate connectedness of the real estate firms to banks shows the fraction

[9] In this study, we refer to the risks of expected real estate prices changes to banks as the risks of the real estate market to banks.

of forecast error variance of the equity returns on banks that can be attributed to shocks in the discount rates.

5.3. Effects of the real estate regulatory policies

To analyze the effects of the real estate regulatory policies, we use regression analysis. Our main interest is to study whether the real estate regulatory policies affect the risks of the real estate market to banks. Firstly, we compare the average cash flow connectedness during "controlling periods" and "stimulating periods" by running the following regression:

$$C_{cf,t} = \beta_0 + \beta_1 D_{c,t} + \varepsilon_t \ , \quad (5)$$

where $C_{cf,t}$ is the cash flow connectedness from real estate firms to banks at month *t*; β_0 and β_1 are the parameters; ε_t is the error term; $D_{c,t}$ is a dummy variable, which is set to 1 during controlling periods; the controlling periods are 2005-Jul. 2008, Dec. 2009-May 2014, and Oct. 2016-2017, and the stimulating periods are Aug. 2008-Nov. 2009 and Jun. 2014-Sep. 2016. In Eq. (5), β_1>0 implies higher risks of the real estate market to banks during controlling periods relative to the stimulating periods, and vice versa.

Secondly, we examine the cash flow connectedness during "controlling months" and "stimulating months", by estimating a similar regression as Eq. (5). Here, we add a dummy variable $D_{s,t}$ and set $D_{c,t}$ and $D_{s,t}$ to 1 during the controlling months and stimulating months respectively. To account for the lag of the policy effect, we also include the month following a policy announcement as a controlling or stimulating month: if a controlling (stimulating) policy were announced before the end of a month, the current month and the next month are defined as the controlling (stimulating) month; if a controlling (stimulating) policy were announced at the end of a month, only the next month is defined as the controlling (stimulating) month. Similar to Eq. (5), a positive coefficient estimate for $D_{c,t}$ ($D_{s,t}$) implies higher risks of the real estate market to banks during the controlling months (during the stimulating months) relative to the months when there was no regulatory policies issued.

Thirdly, we estimate the effects of the four types of real estate regulatory policies by the following regression:

$$C_{cf,t} = \beta_0 + \beta_1 D_{F,t} + \beta_2 D_{T,t} + \beta_3 D_{L,t} + \beta_4 D_{I,t} + \mu_1 D^{+}_{F,t} + \mu_2 D^{+}_{T,t} + \mu_3 D^{+}_{I,t} + \varepsilon_t, \quad (6)$$

where β_i and μ_j (i=0, 1, 2, 3, 4; j=1, 2, 3) are the parameters; $D_{F,t}$, $D_{T,t}$, $D_{L,t}$, and $D_{I,t}$ are the dummy variables for the financial policies, tax policies, land policies, and industrial policies respectively during the real estate controlling periods (see table 1 in the appendix) ; $D^{+}_{F,t}$, $D^{+}_{T,t}$, and $D^{+}_{I,t}$ are the dummy variables for the financial policies, tax policies, and industrial policies respectively during the real estate stimulating periods (see table 1 in the appendix). Similar to the dummy variables for the controlling months and stimulating months above, we set the corresponding type of policy dummy to 1 for the month following the policy announcement and the month when the policy was announced (if the announcement did not occur at the end of the month). In Eq. (6) above and Eq. (7) below, β_i>0 or μ_j>0 (i=1, 2, 3, 4; j=1, 2, 3) indicates higher risks of the real estate market to banks when the corresponding type of policies were issued, relative to the months when there was no regulatory policies issued.

Fourthly, we control for the impact of the market volatilities and real estate prices and re-estimate the effects of the four types of real estate regulatory policies. Previous studies suggest that during market turmoil when the market volatilities are high, assets connectedness tends to be stronger (see e.g., Yang et al. 2003, Cheung et al. 2010). Moreover, real estate regulatory policies could be correlated with the level of real estate prices, as there is a higher probability that the Chinese government would introduce real estate control policies when the real estate prices are higher. Therefore, we include market volatility and real estate price as two additional control variables and estimate the following regression:[10]

$$C_{cf,t} = \beta_0 + \beta_1 D_{F,t} + \beta_2 D_{T,t} + \beta_3 D_{L,t} + \beta_4 D_{I,t} + \mu_1 D_{F,t}^{+} + \mu_2 D_{T,t}^{+} + \mu_3 D_{I,t}^{+} + \Sigma_{i=1}^{2} h_i x_{i,t} + \varepsilon_t, \quad (7)$$

where h_i (i=1,2) is the parameter; $x_{1,t}$ and $x_{2,t}$ are the market volatility and real estate price change (in percentages) at month t, respectively.

In addition, we also examine the effects of the four types of real estate regulatory policies on the overall return connectedness and discount rate connectedness from the real estate firms to banks. In particular, we change the dependent variable to overall return connectedness (or discount rate connectedness) from the real estate firms to banks and re-estimate Eqs. (6) and (7).

6. Empirical results

Table 1 reports the parameter estimates of the VAR(1) model in Eq. (2), which are used to compute the two return components of the real estate firms. Four state variables are included in the VAR model: log excess return of the real estate firms, log dividend-yield of the real estate firms, term-spread, and small-stock value spread. The parameter estimates for the excess return equation show that dividend-yield positively predicts the excess return of the real estate firms.

[10] We use the realized volatility of SSE 50 index (excluding all the real estate firms and banks) to represent the market volatility. For the overall real estate prices, we downloaded from Datasteam the real estate transaction data by China Index Academy in 24 Chinese cities: Baotou, Beijing, Changsha, Chengdu, Chongqing, Dalian, Dongguan, Fuzhou, Guangzhou, Haikou, Hangzhou, Ningbo, Qingdao, Shanghai, Shantou, Shaoguan, Shaoxing, Shenyang, Shenzhen, Suzhou, Tianjin, Wuhan, Wuxi, and Xi'an. The transaction data are for the commercial residential buildings (five missing values are replaced by the average of the values in the previous month and following month). We represent the overall real estate prices in China by a weighted value of the average transaction prices in the 24 cities, with the weights being the transaction area in each city. Due to the availability of the real estate price data, the sample period here starts from February 2009.

Past excess return of the real estate firms and small-stock value spread have similar levels of predictability for the future excess return of the real estate firms, although the results are not statistically significant. The positive predictive power of the dividend-yield for the returns of the real estate firms is consistent with the result for the aggregate market returns in Engsted et al. (2012). The proportion of return variance explained by the four state variables is 3.8%, which is higher than the corresponding number of 2.57% in Campbell and Vuolteenaho (2004). The coefficient estimates for the dividend-yield equation suggest the high persistency of the dividend-yields of the real estate firms. The estimates for the equations of the other two state variables (term-spread and small-stock value spread) indicate that past return and dividend-yield of the real estate firms and past term-spread can predict the future term-spread, while past return of the real estate firms and small-stock value spread have some predictive power for the future small-stock value spread.

[Table 1 near here]

Figure 1 shows the dynamic overall return connectedness, discount rate connectedness, and cash flow connectedness of the real estate firms to banks. The three connectedness measures are computed based on forecast error variance decompositions with a rolling window of 36 months and a forecast horizon of 6 months. Overall return connectedness of the real estate firms to banks showed large fluctuations from 2005 to June 2007 and from April 2012 to November 2013. Following a relatively stable period from July 2007 to April 2008, overall return connectedness gradually increased, reaching a level of around 29% in March 2012. Overall return connectedness showed another rising trend from the beginning of 2014 to September 2015, after which it started to decline slowly until the end of the sample period.

[Figure 1 near here]

In general, overall return connectedness from the real estate firms to banks did not show any distinct trend during the controlling periods, except for the last controlling period from October 2016 to October 2017, during which it decreased slowly. However, the overall return connectedness seems to be increasing gradually during the first stimulating period from August 2008 to November 2009. Over the second stimulating period from June 2014 to September 2016, overall return connectedness also showed a strong increase from October 2014 to September 2015. Therefore, the dynamic overall return connectedness of the real estate firms to banks suggests that real estate regulatory policies aiming at supporting or stimulating the real estate market would likely increase the overall risks of the real estate firms to banks.

Regarding the discount rate connectedness of the real estate firms to banks, during the first controlling period, it first surged in 2005 and then declined rapidly until August 2006. The discount rate connectedness displayed a strong upward trend from April 2008 to May 2010 and a significant downward trend at the end of the sample period from May 2015 to 2017. Overall, the discount rate connectedness intensified during the first stimulating period from August 2008 to November 2009 and slightly decreased during the last controlling period from October 2016 to 2017.

Despite of the real estate control policies, cash flow connectedness of the real estate firms to banks increased from 2005 to March 2008. The cash flow connectedness then decreased steadily, reaching the lowest level at the end of 2012. In 2013 and 2015, the cash flow connectedness was largely increasing. After a drop during the first half of 2016, the cash flow connectedness remained stable until the end of the sample period. Overall, during the first controlling period from 2005 to July 2008, the cash flow connectedness was generally increasing (from 2005 to March 2008). However, during the second controlling period from December 2009 to May 2014, the cash flow connectedness was largely decreasing (from December 2009 to December 2012), while during the last controlling period from October 2016 to 2017, the cash flow connectedness was stable. On the other hand, the cash flow connectedness was generally decreasing during the first stimulating period, but it did not display any trend during the second stimulating period. Hence, the dynamic cash flow connectedness of the real estate firms to banks does not provide clear evidence about the effects of the real estate regulatory policies on constraining the real estate market risks to banks.

To further examine the effects of the real estate regulatory policies, we run a few regressions. Table 2 reports the results of the regression analysis. Our main interest is to study the effects of the real estate regulatory policies on the cash flow connectedness of the real estate firms to banks (or the risks of the real estate market to banks). Table 2 shows that compared to the stimulating periods, the average cash flow connectedness of the real estate firms to banks is lower during the controlling periods, although the difference is not statistically significant. Relative to the months when there were no real estate regulatory policies announced, the average cash flow connectedness of the real estate firms to banks is higher during the months when there were real estate stimulating policies announced. Interestingly, none of the four types of real estate control policies has effect on the cash flow connectedness of the real estate firms to banks. Among the four types of real estate stimulating policies, tax policies appear to increase the cash flow connectedness. Therefore, the results in table 2 suggest that real estate control policies cannot constrain the risks of the real estate market to banks. On the other hand, real estate regulatory policies aiming at supporting or stimulating the real estate market can increase the risks of the real estate market to banks; this increase of risks of the real estate market to banks mainly results from the relaxation of tax policies during the stimulating periods. The finding that relaxation of tax policies raises the risks of the real estate market to banks contrasts with the conclusion of Kuttner and Shim (2013) that tax reductions have no significant effect on house prices.

[Table 2 near here]

For the discount rate connectedness of the real estate firms to banks, table 2 shows that it is related to two types of real estate control policies: financial policies and industrial policies. Financial control policies increase the discount rate connectedness of the real estate firms to banks, while industrial control policies decrease the discount rate connectedness of the real estate firms to banks. Financial control policies mainly intend to control the real estate market by increasing the interest rates of the mortgage loans, which would increase the expected future discount rates of the real estate firms and thus the discount rate connectedness of the real estate firms to banks.

Table 2 also shows that two types of real estate control policies (land policies and industrial policies) and two types of real estate stimulating policies (financial policies and tax policies) affect the overall return connectedness of the real estate firms to banks. Similar for the case of cash flow connectedness, tax-type stimulating policies or relaxation of tax policies increases the overall return connectedness of the real estate firms to banks. In contrast, financial stimulating policies or relaxation of financial policies decreases the overall return connectedness of the real estate firms to banks. When the policy makers in China relax the financial policies by decreasing the interest rate and the requirement of down payment for the mortgage loans, financing constraints of the homebuyers and real estate firms are relaxed. Consequently, the overall risks of the real estate firms to banks decrease. This finding is also consistent with the result of Zhang et al. (2016) that lower growth rate of real estate investment increases bank instability, since real estate investment would likely increase when the relaxation of financial policies leads to less financing constraints for the homebuyers and real estate firms.

Among the four types of real estate control policies, industrial policies increase the overall risks of the real estate firms to banks. Unlike the industrial control policies, land control policies decrease the overall risks of the real estate firms to banks. Land control policies could reduce the supply of land and thus increase the value of the lands and homes held by the real estate firms, decreasing the risks of the real estate firms to banks. This finding of significant impact of the land control policies is also in line with Zhang (2008).

For all the three connectedness measures, the estimated coefficient for the market volatility is always positive and statistically significant, which is consistent with previous finding that during market turmoil when the market volatilities are high, assets connectedness tends to be stronger. The overall housing price changes, in contrast, do not appear to be related to the overall return connectedness, the discount rate connectedness or the cash flow connectedness of the real estate firms to banks, implying that market participants do not associate high real estate prices with high real estate risks to banks. Two of the three connectedness measures (overall return connectedness and discount rate connectedness of the real estate firms to banks) are affected by the real estate control policies. This result is in line with the finding of Wang and Sun (2013) that house-related policies in China can help to constrain excessive house price growth.

7. Conclusion

In this study, we investigate whether the real estate regulatory policies issued by the Chinese policy makers can constrain the real estate risks to banks in China. Specifically, by the framework of Campbell (1991), we first decompose the equity returns of the Chinese real estate firms into a discount rate news component and a cash flow news component. By the connectedness measure of Diebold and Yilmaz (2014), we then study the overall return connectedness from the real estate firms to banks, the connectedness of the discount rate news component of the real estate firms to banks, and the connectedness of the cash flow news component of the real estate firms to banks. We interpret the overall return connectedness, the discount rate connectedness, and the cash flow connectedness of the real estate firms to banks as the overall risks of the real estate firms to banks, the discount rate risks of the real estate firms to banks, and the risks of the real estate market to banks, respectively. Finally, we examine the effects of real estate regulatory policies on these three types of real estate risks to banks.

Our study shows that dynamic overall return connectedness of the real estate firms to banks displayed some rising trend during the real estate stimulating periods, which suggests that real estate regulatory policies aiming at supporting or stimulating the real estate market could increase the overall risks of the real estate firms to banks. The study also shows that two types of real estate control policies (land policies and industrial policies) and two types of real estate stimulating policies (financial policies and tax policies) can affect the overall risks of the real estate firms to banks. The discount rate risks of the real estate firms to banks, however, are only affected by two types of real estate control policies: financial policies and industrial policies. Unexpectedly, real estate control policies do not seem to be able to constrain the risks of the real estate market to banks. Real estate stimulating policies, on the other hand, show some effects of raising the risks of the real estate market to banks, which mainly results from the effects of tax-related stimulating policies.

From the perspective of real estate market regulations, the relaxation of tax-related real estate regulatory policies would increase both the overall risks of the real estate firms to banks and the risks of the real estate market to banks. The relaxation of financial regulatory policies can reduce the overall risks of the real estate firms to banks, while financial control policies would increase the discount rate risks of the real estate firms to banks. Land-related real estate control policies can decrease the overall risks of the real estate firms to banks. Industry-related real estate control policies could lead to higher overall risks but lower discount rate risks of the real estate firms to banks. In this study, we only analyze the effects of real estate regulatory policies on the real estate risks to banks in China. Future research could study the spillovers of the effects of real estate regulatory policies issued by one country to other countries.

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Appendix:

Table 1. Major real estate regulatory policies in China from 2005 to 2017.

Time	Policy issuer	Main features of the policy
Major real estate regulatory policies from 2005 to July 2008 (controlling period)		
Financial policy:		
Mar. 2005	PBC	Adjusting the interest rates of mortgage loans and housing provident fund loans; increasing the down payment ratio in regions with rapid housing price growth
Sep. 2007	PBC and CBRC	Adjusting the interest rates and down payment requirements of mortgage loans by commercial banks
Tax policy:		
May 2005	SAT, MF, and MoC	Full sales tax payment required when a house bought within 2 years is sold
Land policy:		
Jul./ Aug. 2006	SC and MLR	Regulating the approval of land usage; controlling the transferring of agricultural land to real estate land; prohibiting illegally lowering land sales price; further strengthening the regulations of land sales and usage
Industrial policy:		
Mar. 2005	SC	Emphasizing the importance of stabilizing the housing prices
May 2006	SC	Stabilizing the housing prices from different aspects: loans, construction of economical housing , etc.
Jul. 2006	MoC etc.	Strengthening the management of foreign investments in real estate markets; restricting the housing purchases of foreign organizations and persons
May 2007	MC and SAFE	Strengthening the approval and monitoring of foreign investments in real estate markets
Aug. 2007	SC	Requiring resolution of the housing problems facing urban low-income families
Major real estate regulatory policies from August 2008 to November 2009 (stimulating period)		
Financial policy:		
Oct. 2008	PBC	Decreasing the interest rates of commercial personal mortgage loans and the ratio of down payment
Jul. 2009	CBRC	Strongly supporting the loan demands of borrowers buying the first house or meeting the standards of housing improvement

Table 1 (continued)

Tax policy:		
Oct. 2008	MF and SAT	Reducing the rate of deed tax to 1% for purchasing the first house not larger than 90 square meters
Dec. 2008	SAT and MF	Sales tax is exempted when an ordinary house owned for more than 2 years is sold
Nov. 2009	SAT	When a person subleases a house, the rent income is subject to personal income tax
Industrial policy:		
Aug. 2008	MHURD, NDRC, and MF	Increasing the number of low-rent houses to 3.5 million from 1 million
Dec. 2008	SC	Increasing the construction of low-income housing; further increasing the support of demands for housing loans
Major real estate regulatory policies from December 2009 to May 2014 (controlling period)		
Financial policy:		
Feb. 2010	CBRC	Regulating the use of working capital loans
Apr. 2010	CBRC and SC	Regulations about the issuance of housing loans to speculators, second-house or third-house buyers, and non-local residents
Jun. 2010	MHURD, PBC, and CBRC	Clarifying the criteria for identifying the number of houses of a family
Jul. 2010	CBRC	Emphasizing the strict implementation of differential mortgage policies
Nov. 2010	MHURD, MF,PBC, and CBRC	Ending the provident fund loans for third houses and increasing the down payment for second houses
Jul. 2013	SC	Guidelines for implementing the real estate control policies and differential housing credit policies and preventing real estate financing risks
Tax policy:		
Dec. 2009	SC,MF, and SAT	Regulations about the housing transfer sales taxes, with the exemption period increased from 2 years to 5 years
Land policy:		
Dec. 2009	MF, etc.	Full payment for acquired lands within 1 year (or 2 years for special projects, with the first payment no less than 50% of the total price)
Mar. 2010	MLR	Regulating the supply and inspection of housing land

Table 1 (continued)

Aug. 2010	MLR and CBRC	MLR created a blacklist of 1457 parcels of idle land. Based on the assessment of risks by CBRC, 80% of those idle land could be reclaimed
Sep. 2010	MLR and MHURD	Tightening the management of real estate land and construction; firms with lands idle for more than 1 year cannot bid for new lands
Sep. 2012	MLR and MHURD	Increasing the supply of land; improving the land transaction methods; emphasizing the enforcements of existing policies
Industrial policy:		
Dec. 2009	SC	Regulations about effective supply of housing, housing ownership and speculation, market supervision, and affordable housing construction
Jan. 2010	SC	Calling for further control of the real estate market and highlighting the steady and healthy development of the real estate market
Mar. 2010	SASAC	78 central enterprises whose primary business is not real estate development were required to withdraw from real estate business
Apr. 2010	MHURD and SC	Regulations about construction of affordable housing, curbing price growth, and issues related to housing sale system and housing credit policy
Jun. 2010	MHURD,etc.	Promoting the development of public rental housing
Sep. 2010	Premier Li and several government departments	Regulations about construction of affordable and public rental housing, mortgage loans, restrictions on the number of houses a family or resident can buy in certain cities, and taxes in housing transactions
Jan. 2011	SC	Comprehensive regulations about local government responsibility, affordable housing, tax issues, housing credit policy, etc.
Feb. 2013	SC	Curbing speculative housing demand, increasing housing and land supply, promoting affordable housing, and seeking long-term development mechanism of the housing market
Major real estate regulatory policies from June 2014 to September 2016 (stimulating period)		
Financial policy:		
Sep. 2014	PBC and CBRC	Adjusting the housing credit policy
Mar. 2015	PBC, MHURD, and CBRC	Reducing the ratio of down payment for second house purchases to 40%; for first house purchases, down payment ratio of provident fund loans adjusted to 20%
Tax policy:		
Mar. 2015	MF and SAT	Sales tax exemption period for second-hand house transactions was reduced from 5 years to 2 years

Table 1 (continued)

Feb. 2016	MF,SAT, and MHURD	Reducing the deed tax and sales tax for housing transactions
Industrial policy:		
Jun. 2014	Hohhot government	Hohhot became the first city to lift the restrictions on housing purchases
Major real estate regulatory policies from October 2016 to 2017 (controlling period)		
Industrial policy:		
Sep. 2016	Local governments	20 cities issued real estate control policies, including restrictions on housing purchases and loans
Mar.-May 2017	Local governments	From March to May, many cities introduced regulatory policies, including restrictions on housing purchases, loans and sales.
Sep.-Nov. 2017	Local governments	In September, 11 second tier cities deepened the control policies; From October to November, some third and fourth tier cities regulated the housing market mainly by restrictions on sales

Notes: this table shows the major real estate regulatory policies in China from 2005 to 2017, which is compiled from three previous studies by China Index Academy (2017), He (2016, 107–112), and Ren (2017). Abbreviations of the names of the policy issuers are used for People's Bank of China (PBC), China Banking Regulatory Commission (CBRC), State Council (SC), State Administration of Taxation (SAT), Ministry of Finance (MF), Ministry of Construction (MoC), Ministry of Commerce (MC), State Administration of Foreign Exchange (SAFE), Ministry of Housing and Urban-Rural development (MHURD), National development and Reform Commission (NDRC), Ministry of Land and Resources (MLR), and State-owned Assets Supervision and Administration Commission of the State Council (SASAC). The month is shown in boldface when the policy was announced at the end of that month (we define the policy was announced at the end of the month if there were less than 5 trading days in the month after the policy announcement date).

Table 1. VAR parameter estimates for the returns of the real estate firms.

	Constant	$R^e_{RE,t}$	dp_t	TS_t	VS_t	R^2
$R^e_{RE,t+1}$	0.1422	0.1004	0.0323	1.1461	0.1040	0.0380
	(2.0914)	(1.3800)	(2.0166)	(0.8060)	(1.3782)	
dp_{t+1}	-0.1265	-0.0399	0.9689	-1.0759	0.0108	0.9390
	(-1.4162)	(-0.4174)	(46.0908)	(-0.5760)	(0.1093)	
TS_{t+1}	-0.0023	0.0058	-0.0009	0.8432	-0.0005	0.7883
	(-1.2558)	(2.8956)	(-2.0494)	(21.7156)	(-0.2304)	
VS_{t+1}	-0.0328	-0.0451	-0.0064	-0.0471	0.8913	0.8458
	(-1.2829)	(-1.6457)	(-1.0573)	(-0.0880)	(31.3883)	

Notes: the table reports the parameter estimates of the VAR (1) model in Eq. (2) for the returns of the real estate firms. $R^e_{RE,t+1}$ is the log excess return of the real estate firms at month *t*+1, dp_{t+1} is the log dividend-yield of the real estate firms at month *t*+1, TS_{t+1} is the term-spread at month *t*+1, and VS_{t+1} is the small-stock value spread at month *t*+1. The first row, third row, fifth row, and seventh row show the parameter estimates for the equation of log excess return, log dividend-yield, term-spread, and small-stock value spread, respectively. T-statistics are shown in the parentheses.

Table 2. Estimates of the effects of the real estate regulatory policies.

	CF	CF	CF	CF	DR	DR	RET	RET
Constant	7.97***	7.13***	7.20***	3.40***	15.05***	17.16***	24.35***	25.54***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C_Periods	-0.69							
	(0.44)							
C_Months		0.44						
		(0.64)						
S_Months		2.45*						
		(0.07)						
C_Financial Policies			-1.46	0.83	3.13	2.38**	0.03	-1.02
			(0.32)	(0.42)	(0.11)	(0.02)	(0.99)	(0.31)
C_Tax Policies			-3.05	1.05	0.80	1.88	-3.75	-2.48
			(0.33)	(0.69)	(0.85)	(0.46)	(0.24)	(0.33)
C_Land Policies			-0.54	-1.55	1.42	0.70	-0.72	-2.76**
			(0.75)	(0.22)	(0.53)	(0.57)	(0.67)	(0.02)
C_Industrial Policies			1.64	1.25	-2.09	-1.52*	0.62	2.16***
			(0.16)	(0.16)	(0.18)	(0.08)	(0.60)	(0.01)
S_Financial Policies			-0.57	0.17	1.37	-1.40	-0.28	-2.60*
			(0.81)	(0.91)	(0.67)	(0.36)	(0.91)	(0.09)
S_Tax Policies			3.29	2.74*	2.23	1.58	3.36	3.35**
			(0.12)	(0.10)	(0.43)	(0.33)	(0.12)	(0.04)
S_Industrial Policies			2.31	-0.29	-1.54	0.31	-1.84	-1.87
			(0.28)	(0.89)	(0.59)	(0.88)	(0.39)	(0.37)
Market Volatility				25.75***		29.65***		22.50***
				(0.01)		(0.00)		(0.01)
House Price Change				0.00		-0.01		0.02
				(0.95)		(0.86)		(0.77)

Notes: the table reports the OLS estimates of the time series regression analysis for the effects of the real estate regulatory policies. The dependent variable, shown in the first row, is the dynamic cash flow connectedness (CF), discount rate connectedness (DR), or overall return connectedness (RET) of the real estate firms to banks. The independent variables are shown in the first column, where "C_" stands for "Controlling" (for example, "C_Periods" is "Controlling Periods"), and "S_" stand for "Stimulating" (for example, "S_Months" is "Stimulating Months"). Due to the availability of the real estate price data, the sample period for the regressions that control for market volatility and overall real estate price changes starts from February 2009. P-values are shown in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance level, respectively.

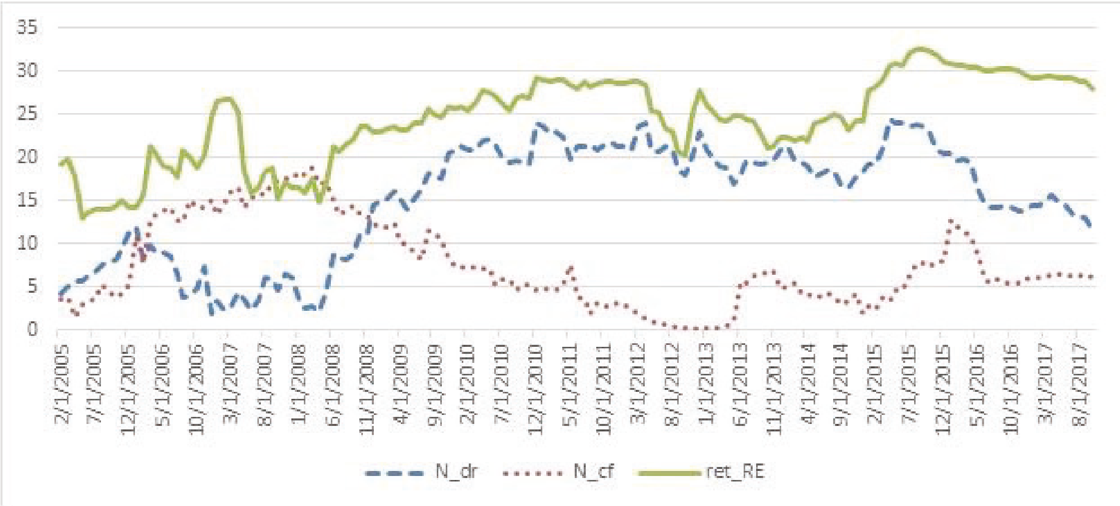

Figure 1. Dynamic overall return connectedness (ret_RE), discount rate connectedness (N_dr), and cash flow connectedness (N_cf) of the real estate firms to banks. The three connectedness measures are computed based on forecast error variance decompositions with a rolling window of 36 months and a forecast horizon of 6 months.