Research article

Volatility connectedness and market dependence across major financial markets in China economy

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Abstract: With the increasing openness of the China economy, the goal of this paper is to examine volatility connectedness and spillover transmissions across markets for stock, public real estate, bond, commodity futures, and foreign exchange within the China economy. Over the full study period, we find that the five China's financial markets are not strongly volatility connected. The bond market is the predominant market of spillover transmission, whereas the commodity futures market is the top net recipient of volatility connectedness shocks. The role of spillover transmission increased during the three financial crisis periods studied. Additionally, the five markets display some degree of nonlinear causal dependence. During the Chinese stock market crash, the stock and public real estate reacted with similar patterns and larger positive or negative responses to shocks, whereas bonds and commodity futures have milder shocks response. Our findings have important implications for portfolio investors in asset diversification and policymakers in their domestic macroprudential policy coordination and control.

1. Introduction

Are major domestic financial markets significantly volatility connected in the China economy? Do the shocks originate in one market spillover to other markets? A good understanding of the spillover-connectedness (Diebold and Yilmaz, 2012, 2014) across different domestic financial markets within a domestic economy is an important consideration when designing investment portfolios. This is even unique for China since one key institutional feature that may influence the relations among the China's financial markets was the opening-up of trade and investment since 1978, which provided key support for financial market growth and the development of her expanding economy. The China economy was then affected by the 2008–2009 global financial crisis (GFC) and the subsequent European financial crisis (EFC), as well as the mid-2015 domestic stock market crash (STCRASH).

As China is now accelerating its loosening of various capital control measures and promoting the further opening of its domestic markets, its financial markets have attracted growing interest from domestic and international investors. Foreign investors are interested in not only their stock and currency markets but also other asset classes such as bonds, commodity futures, and real estate investments due to their huge size and potential diversification benefit. In addition, an excess spillover across the asset classes tends to be a signal of market uncertainty. Since China has numerous trading partners across the World, a turbulent state of the Chinese market significantly affects other countries (Majdoub and Sassi, 2017; Liow et al., 2019; Ahmed and Huo, 2019). Thus, investigating the major domestic financial markets' spillover-connectedness within the Chinese economy provides important information to foreign and global investors who hold multi-asset portfolios across China and multiple countries.

Using a dataset from November 2005 to October 2018,[1] this study empirically examines the dynamics of volatility connectedness and spillover transmission in five major domestic financial markets in the China economy for understanding the transmission mechanism of risk transfer. The five asset classes we investigate comprise a major part of the Chinese financial market and should have a significant impact on cross-asset market relationships and dependence. Based on Diebold and Yilmaz (Diebold and Yılmaz, 2012, 2014), we examine the dynamic volatility spillover-connectedness among the Chinese stock market, public real estate market, bond market, commodity futures market, and foreign exchange market.

The Chinese stock market, launched in 1990, has become the World's second-largest capital market, with the total market capitalization of the Shanghai Stock Exchange valued at USD $5 trillion in 2018. China's foreign exchange market has become more influential worldwide, and the RMB is becoming a new strong world currency. In the stock market, there have been several mechanisms, such as herding behavior, wealth effect, and irrational expectation, that potentially trigger the asset market spillovers (e.g., Ju, 2020). The information from the foreign exchange market is of central importance for trading activity in the China market because of the solid connection of trades between China and numerous foreign countries. Its bond market (Treasury bond and local government bonds) is the third-largest in the World, with a volume of about USD 6.91 trillion as of the end of 2005 (Wang et al., 2016). In the history of the financial market, the bond market has shown a crucial role during volatile periods because investors are

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[1]The Chinese currency, RMB only stopped pegging at US dollar since mid-2005. Hence the series is quite stable, with almost no change at all before October 2005. This consideration has dictated the common study period for the study to start on Nov 1, 2005.

more risk-averse and follow "flight-to-quality" (Vayanos, 2004). Chinese future exchange was established jointly by the three commodity futures markets (mainly traded in Shanghai future exchange, Zhengzhou commodity exchange, and Dalian commodity exchange) and two stock exchanges in 2006. China's commodity future market became the World's largest in 2009, with the trading contracts reached 2.29 billion in 2014 (Wang et al., 2016). Moreover, it has been empirically documented that commodity futures can diversify the risks of stock and bond markets (Gorton and Rouwehorst, 2006). The four asset classes (stocks, foreign exchanges, bonds, and commodity futures) have been the four main markets explored in prior literature because of their crucial influence on each other. Finally, the emerging public real estate sector of China is a prominent part of the Chinese economy as it contributed 6.5% to the overall GDP in 2016 and is one of the biggest recipients of foreign direct investment in China (Fung et al., 2006).

We first conduct volatility spillover analysis across the five financial markets to examine how five financial markets in China are connected via second-moment shocks. We then use the contagion theory to explain the information transmission change during the financial crisis periods, as well as to test whether a stronger connection is observed during volatile periods.[2] Since volatility connectedness is a function of market dependence, we also implement Granger causality tests (both linear and nonlinear) to understand which financial market has strong volatility causal dependence with others. Finally, selective generalized impulse response function analysis is exploited to obtain additional insights into the transmitting mechanism of the asset market movements during the 2015 Chinese stock market crash (STCRASH).

One major contribution of this study is that this is probably one of the very few studies to provide a fuller understanding of the dynamic volatility spillover-connectedness within the China economy, an economic system that has evolved differently from other Asian emerging economies and other advanced economies, in terms of economic growth, economic reform and financial market deregulation and globalization.[3]

Our second academic contribution is, different from the conventional studies, which confined mainly to stock, bond, and foreign exchange markets, the inclusion of public (securitized) real estate market in this study reflects the increasingly important role of this new "asset" class in the China economy irrespective of the fact that the size of the real estate market is much bigger within the China economy. This is particularly the case when public real estate has become an important tool for international diversification among stocks, bonds, foreign exchanges, economic growth, and the GFC. The volatility connectedness role of public real estate was evident during the GFC. This significant development has led Dhar and Goetmann (2006) to recognize that public real estate was an "essential" asset class in investors' mixed-asset portfolios, in addition to its existing role as an "industry" of the domestic stock market. Moreover, international public real estate diversification may be more effective than international stock market diversification (Eichholtz, 1986).

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[2]Forbes and Ribogon (2002) define contagion as a "significant increase" in cross-market linkages that results from shocks hitting one country (or group of countries).

[3]During the last two decades, China's economy has emerged as a major power in the world economy (Wang et al., 2016). With its high GPP growth, China has passed Japan to become the world's 2nd largest economy. Moreover, China's economic reform has gradually shifted toward liberalization of financial markets and intensified its interactions with the global financial markets. Consequently, its financial markets have attracted growing interest from domestic and international investors.

Third, although the volatility spillover-connectedness over the GFC and EDC have been well covered in the literature, there is insufficient knowledge regarding the impact of STCRASH on volatility transmission and connectedness (Ahmed and Huo, 2019).[4] Investigating market spillover-connectedness is important for domestic and foreign investors during the 2015 STCRASH since its first domestic market depression during the modern era of the China financial markets.

Fourth, although linear tests of Granger causality have been investigated very deeply due to its straightforward economic interpretation, they are limited in their capability to detect nonlinear causality (Bai et al., 2010). Hiemstra and Jones (1994) posited that studying the intertemporal relation in higher-order shocks is of central importance for capturing complete information of asset market dependence. Using the usual Granger linear and nonlinear Granger causality test of Dicks and Panchenko (2006), our specific methodological contribution is that we indicate that a better understanding of the domestic asset market dependence should also consider the nonlinear feature of the causal link in the 2nd moment (volatility), in addition to the usual nonlinear causal link in the first moment (returns). To our knowledge, we are of the very few who links volatility connectedness and market dependence empirically.

Overall, our results are particularly useful for local investors in China and their policymakers. By understanding the dynamics of volatility connectedness and causal volatility dependence in domestic financial markets, investors can improve their design of portfolio diversification and hedging strategies. Additionally, understanding which markets are, respectively, net "senders" and net "recipients" of volatility transmission in the China economy is essential when assessing risk and market stability and formulating regulatory control measures by policymakers (Wang et al., 2016).

The remainder of the paper is organized as follows. Section 2 provides an updated literature review and identifies some knowledge gap(s) on this topic. Section 3 explains the data requirement. With the empirical methodologies and fuller discussion of the results that follow, the last section concludes the study.

2. Literature review and knowledge gap

An increasing body of studies has focused on the market links of the Chinese stock market with regional or global stock markets using different time series short-term and long-run statistical methodologies. Together with the US and Japan, one focus was to evaluate the stock market interdependence between China and Asian-Pacific markets, as well as how the links have shifted during and after the 1997–1998 Asian Financial Crisis (AFC) and the 2008–2009 GFC. These studies include Ng (2000), Yilmaz (2010), Burdekin and Siklos (2011), Glick and Hutchinson (2013), Tam (2014), Chien et al. (2015), and Zhou et al. (2012). For example, Glick and Hutchinson (2013) find that the strength of the correlation of stock returns between China and other Asia countries increased markedly during the GFC and has remained high in recent years.

A cross-asset spillover is one of the important topics in finance due to investors who hold diversified assets based on asset characteristics. There have been many empirical pieces of literature that explore the cross-asset spillovers in the financial market using different sets of asset classes. For

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[4]Most studies associated with China "STCRASH" focused on the cross-border impact of the Chinese stock market with other countries. There is limited coverage on the domestic financial market impact of the China 2015 STCRASH.

example, recent studies consider new asset classes, such as green bonds and cryptocurrencies, as well as traditional asset classes, such as government bonds, stock (e.g., Huynh, 2020; Huynh et al., 2020). In the area of domestic volatility spillover-connectedness, Li and Zhou (2008), Zhao (2010), Weber and Zhang (2012), and Wang et al. (2016) have investigated this topic in the Chinese stock, bond, commodity futures, and foreign exchange markets in different combinations. However, so far, none of the studies have investigated the volatility spillover-connectedness simultaneously across the five financial markets in China, similar in scope to the present study. The nearest exception is by Wang et al. (2016), who examine volatility spillovers across the Chinese stock, bond, commodity futures, and foreign exchange markets using the spillover index method. In contrast, our study is much wider in scope in that we also include its public real estate market to explore the volatility connectedness role and market dependence.

In terms of methodological frameworks, various spillover approaches have been introduced in empirical finance literature. Among many others, most studies tend to focus on exploring extreme risk dependence or second-moment linkage. For the extreme risk dependence, copula has received much attention. For example, Huynh et al. (2020) investigate the spillovers across green bonds and cryptocurrencies by using copulas. Hyunh (2020) exploit Student's t-copulas to examine the tail dependence among green bonds and government bonds. However, the second-moment linkage is more widely adopted in spillover studies. In so far as this study is concerned, we note that extensive literature has used Diebold and Yilmaz's (2012) spillover index methodologies to investigate the spillover effects in the US stock, bond, foreign exchange, oil, and to a lesser extent, public real estate market. Diebold and Yilmaz (2014) constructed various connectedness measures based on the generalized forecast error variance decomposition. Other empirical studies include Yilmaz (2010), who investigated the extent of contagion across Southeast Asian stock markets and found evidence of direct linkages, Diebold and Yilmaz (2012) provide an unconditional directional volatility spillover study on the US financial markets' cross-volatility transmission during the GFC, Zhou et al. (2012) on the Chinese and World equity markets, Antonakakis (2012) on Euro five major foreign exchanges, Duncan and Kabundi (2011) on South African foreign exchange, bond and stock, Awartani and Maghyereh (2013) on oil and equities in the GCC countries and Louzis (2013) on money, stock, foreign exchange and bond markets of euro areas. Liow (2015a, 2015b) includes public real estate in his conditional volatility spillover studies across emerging economies and G7 nations. Maghyereh et al. (2015) find volatility spillover for their sample of stock markets increased following the 2008 GFC. They also find that the unidirectional spillover relationship was only pronounced in periods of stress while it was absent during the normal periods. Using a sample of ten real estate investment trusts (REITs) from July 2004 to June 2017, Liow and Huang (2018) find a less similar integration process is taking place in the global REIT markets. The local stock market is a major source of REITs' volatility connectedness shocks in 80 percent of the time. Moreover, the REITs' volatility spillover-connectedness effects are crisis-sensitive and decline more quickly than stocks when the crises went off. This study further investigates the spillover-connectedness behavior during the STCRASH, a Chinese domestic crisis period that should deserve more academic attention since it explores whether an internal uncertainty within a country provides different or similar market relationship behavior in volatility connection.

Overall, there is growing interest in the literature that examines volatility connectedness and causal dependence across major domestic financial markets in the China economy and other countries. However, more needs to be understood about this issue of market dependence, considering that

volatility connectedness among international financial markets can be quite different from the volatility connectedness among domestic financial markets. Moreover, the China economy has become more open at later dates than many of its developed counterparts, such as the USA and Japan. In the context of this study, portfolio investors and policymakers may be ignorant of the current level and anticipated/unexpected changes in the domestic spillover transmission and volatility connectedness during normal and crisis times and their respective influential factors. The major objective of this study is to contribute to a better understanding of these issues empirically.

3. Data

We extract the China Securities Index (CSI) 300 stock index, CSI 300 real estate index, CSI aggregate bond (AB) index, and CSI commodity futures composite (CCF) index as proxies for China's stock public real estate, bond, and commodity futures respectively.[5] These data are retrieved from the Wind info. In addition, we select Chinese Yuan to US $ (WMR, London 4 pm Fix) as a proxy for the foreign exchange market from Datastream. We collect the daily closing values of each index from November 1, 2005, to October 26, 2018, giving a total of 3144 observations.[6] The asset returns are estimated as $R = (\ln P_t - \ln P_{t-1})$, where P_t is the daily closing value of the financial index on day t. The ADF unit root test (results not reported to preserve space) indicates all return series are stationary.

Table 1 provides the usual summary statistics for the five asset classes. The numbers indicate that the public real estate market has the highest unconditional return volatility (daily: 2.393%), followed by the stock market (1.784%), the commodity future market (0.890%), the foreign exchange market (0.145%), and the bond market (0.107%). Panel B indicates that other than the stock and public real estate, which are strongly correlated (correlation coefficient is 0.806), as well as between the stock and commodity futures markets which are moderately correlated (correlated coefficient is 0.340); the remaining eight pairs are either marginally negatively correlated or weakly positively associated.

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[5]We use a public real estate market index as a proxy for real estate market for three reasons. Firstly, the stock price of listed real estate firms can reflect the company's performances, while the real estate firms' performances are closely related to the condition of the direct property market. Second, the data from the direct real estate market is in low frequency, while the public real estate data is the only available source for our empirical analysis in higher frequency. Third, there are many restrictions on direct real estate investment in China, such as housing purchasing restrictions in a few cities and mortgage restrictions. Not every investor has equal access to direct real estate investment. Thus, public real estate firms are very important investment channels for investors who want to share the benefit from the growth of the Chinese housing market.

[6]We focus on these three major financial events, which are explicitly associated with financial markets. We investigated how Chinse financial markets were integrated in response to uncertainties that were mainly driven by changes in financial stability across domestic and cross-borders. Thus, we cover up to ther Chinese stock market crash, which was the most recent major financial turmoil. Although we faced several other events during more recent 2019–2020, such as US-China trade friction or COVID-19, these events were external that indirectly affected financial markets via the real economy channel.

Table 1. Summary of daily returns for China's stock, real estate, bond, commodity futures, and currency markets from November 1, 2005 to October 26, 2018.

	ST	RE	BO	CO	FX
Panel A. Descriptive statistics					
Mean	0.000	0.001	0.000	0.000	0.000
Maximum	0.089	0.095	0.016	0.045	0.018
Minimum	−0.097	−0.105	−0.007	−0.047	−0.011
Std. Dev.	0.018	0.024	0.001	0.009	0.001
Skewness	−0.571	−0.224	1.659	−0.306	0.705
Kurtosis	6.663	5.006	29.591	5.361	19.027
Jarque−Bera	1929.381	553.502	94097.240	779.377	33918.540
Probability	0	0	0	0	0
Panel B. Correlation of unconditional returns					
ST	1.000	0.806	−0.016	0.340	−0.069
RE	0.806	1.000	0.003	0.225	−0.056
BO	−0.016	0.003	1.000	−0.065	0.010
CO	0.340	0.225	−0.065	1.000	−0.087
FX	−0.069	−0.056	0.010	−0.087	1.000

Note: Time-series data is obtained from Wind Info and Datastream.

4. Empirical methodology

This study adopts a four-step procedure. Since the conditional approach is preferred because all five asset returns are not normally distributed, they were first filtered through a multivariate AR (1)-VECH-MGARCH model to obtain the conditional estimates. We restrict the ARCH, GARCH, and TGARCH coefficients to be diagonal in a rank-one matrix-vector format. In addition to the usual conditional variance-covariance spillover coefficients and time-varying correlation coefficients that are generated from the estimations (which are not our focus), the diagonal VECH model estimates the conditional variance (CV) series, which are required for the spillover-connectedness analysis.[7]

Second, with the fitted five-asset markets' CVs obtained from step 1, we employ the generalized VAR framework of Diebold and Yilmaz (2012, 2014) to estimate the total, directional gross, and net volatility spillover-connectedness index measures.[8] For VAR estimation, we choose VAR lag based on the optimal length by the Swartz criterion (SC). Mathematically, assume a covariance stationary N-variable VAR (p):

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_t \tag{1}$$

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances, this VAR model can be written in a moving average (MA) form:

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[7]We obtain parameters for AR(1)-VECH-MGARCH model and use these parameters to estimate conditional variance (conditional volatility) for five-asset markets.

[8]The VAR models examine the decomposition of the forecast error variances through analyzing the total and directional gross and net volatility spillover across the five asset markets, whilst at the same time the results are invariant to the variable ordering (i.e. Generalized VAR modelling).

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_t \tag{2}$$

where A_i is an $N \times N$ coefficients matrix and obeys the recursion $A_i = \Theta_1 A_{i-1} + \Theta_2 A_{i-2} + \cdots + \Theta_p A_{i-p}$, with A_0 an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$.

The variance decomposition transformation of this moving average coefficient uses the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decomposition invariant to the variable ordering. This generalized framework allows for the innovation correlation, which is accounted appropriately using the historically observed distribution of the errors.

Thus, the Z-step-ahead forecast error variance decomposition is:

$$\phi_{ij}^g(Z) = \frac{\sigma_{jj}^{-1} \sum_{z=0}^{Z-1} (\acute{e}_i A_z \Sigma e_j)^2}{\sum_{z=0}^{Z-1} (\acute{e}_i A_z \Sigma \acute{A}_z e_j)} \tag{3}$$

where Σ is the variance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation and e_i is the selection vector, with one as the ith element and zeros otherwise. Following Diebold and Yilmaz (2012), each entry of the variance decomposition matrix is normalized by the row sum to calculate the spillover index from the variance decomposition matrix:

$$\tilde{\phi}_{ij}^g(Z) = \frac{\phi_{ij}^g(Z)}{\sum_{j=1}^{N} \phi_{ij}^g(Z)} \tag{4}$$

The various measures of connectedness dynamics are:

(1) Total connectedness

It is the sum of cross-variance shares, which are the fractions of the Z step-ahead error variances in forecasting x_i due to shocks to x_j. It is estimated as:

$$S^g(Z) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\phi}_{ij}^g(Z)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}^g(Z)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\phi}_{ij}^g(Z)}{N} \times 100 \tag{5}$$

(2) Directional connectedness

It is a measure of the connectedness that captures the shocks received by market i from all markets j:

$$S_{i\cdot}^g(Z) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ij}^g(Z)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}^g(Z)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ij}^g(Z)}{N} \times 100 \tag{6}$$

Similarly, the connectedness from market i to all other markets j are estimated as:

$$S_{\cdot i}^g(Z) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ji}^g(Z)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}^g(Z)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\phi}_{ji}^g(Z)}{N} \times 100 \tag{7}$$

(3) Net connectedness

The difference between $S_{\cdot i}^g(Z)$ and $S_{i\cdot}^g(Z)$ is net connectedness from market i to all other markets j:

$$S_i^g(Z) = S_{\cdot i}^g(Z) - S_{i\cdot}^g(Z) \tag{8}$$

(4) Net pairwise connectedness

It is the difference between the gross volatility shocks transmitted from market i to market j and those transmitted from j to i:

$$S_{ij}^g(Z) = \left(\frac{\tilde{\phi}_{ji}^g(Z)}{\sum_{i,k=1}^N \tilde{\phi}_{ik}^g(Z)} - \frac{\tilde{\phi}_{ij}^g(Z)}{\sum_{j,k=1}^N \tilde{\phi}_{jk}^g(Z)} \right) \times 100 = \left(\frac{\tilde{\phi}_{ji}^g(Z) - \tilde{\phi}_{ij}^g(Z)}{N} \right) \times 100 \quad (9)$$

Third, since volatility is related to market dependence/interdependence and causality, the linear and nonlinear causality interactions on the estimated CVs will reveal which financial markets contribute to the detected causal relationships. Following the literature, Granger (1969) causality tries to test whether knowing the current and lagged values of one market's CVs improves the forecast of future values of each of the other four financial markets' CVs, and vice-versa. However, the linear causality test, while being very popular in the literature, is sensitive to nonlinearity in the data and structural breaks in the time series relationship due to crises, resulting in possible misleading inferences. Following Baek and Brock's (1992) test that propose a nonparametric statistical method for uncovering nonlinear causal relationship, Hiemstra and Jones (1994) modified the test, and subsequently, the test was modified again by the test statistics of Diks and Panchenko (2006). Essentially, the DP nonlinear Granger causality test is applied to the estimated standardized residual series from the VAR model, which can remove any linear predictive power. We provide the mathematical exposition of the methodology as follows.

4.1. Bivariate linear and nonlinear causality tests

We first exploit Granger (1969) linear causality test to investigate intertemporal causality between two variables as follows:

$$X_{1,t} = \alpha_1 + \sum_{i=1}^N \beta_{11,i} X_{1,t-i} + \sum_{i=1}^N \beta_{12,i} X_{2,t-j} + \varepsilon_{1,t} \quad (10)$$

$$X_{2,t} = \alpha_2 + \sum_{i=1}^N \beta_{21,i} X_{1,t-i} + \sum_{i=1}^N \beta_{22,i} X_{2,t-j} + \varepsilon_{2,t} \quad (11)$$

where $X_{1,t}$ and $X_{2,t}$ are conditional volatilities, and N is jointly determined lag order. For the causality running from X_2 to X_1, the null hypothesis is whether $\beta_{12,i}$ is statistically different from zero. If the null hypothesis is rejected, we can argue that X_2 can linearly predict future X_1. In the literature, this relationship indicates that X_2 is granger causing X_1.

However, the linear causality test, while being very popular in the literature, is sensitive to nonlinearity in the data and structural breaks in the time series relationship due to crises, resulting in possible misleading inferences. Following Beck and Brock's (1992) test that proposed a nonparametric statistical method for uncovering nonlinear causal relationships, Hiemstra and Jones (1994) modified the test, which was subsequently modified again by the T_2 test statistics of Diks and Panchenko (2006). Essentially, the DP nonlinear Granger causality test is applied to the estimated standardized residual series from the VAR model, which can remove any linear predictive power. Specifically, the null hypothesis that past information of X_t^{lx} shows no predictive power on Y_{t+1} is:

$H_0: Y_{t+1} | (X_t^{l_X}, Y_t^{l_Y}) \sim Y_{t+1} | Y_t^{l_Y}$ where l_X and l_Y are a finite number of lags, $X_t^{l_X} = (x_{t-lx+1}, x_{t-lx+2}, \dots, x_t)$ and $Y_t^{l_Y} = (y_{t-ly+1}, y_{t-ly+2}, \dots, y_t)$.

The above equation denotes the invariant distribution of the $(lx + ly + 1)$-dimensional vector $W_t = (X_t^{l_X}, Y_t^{l_Y}, Z_t)$ where $Z_t = Y_{t+1}$. Then, the joint probability density function $f_{X,Y,Z}(x, y, z)$ and its marginals must meet the following equation:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)} \tag{12}$$

This equation presumes that X and Z are independent when conditional on $Y = y$. DP (2006) restates this equation as the following null hypothesis:

$$q \equiv E[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)] = 0 \tag{13}$$

Given the local density estimator $\hat{f}_W(W_i) = (2\varepsilon_n)^{-d_w}(n-1)^{-1} \sum_{jj \neq i} I_{ij}^W$ where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon_n)$ with the indicator function $I(\cdot)$ and the bandwidth ε_n, the test statistic is estimated as a scaled sample version of q in the following equation.

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-1)} \cdot \sum_i (\hat{f}_{X,Y,Z}(X,Y,Z)\hat{f}_Y(Y) - \hat{f}_{X,Y}(X,Y)\hat{f}_{Y,Z}(Y,Z)) \tag{14}$$

In the fourth step, we explore the extent to which the shocks from which the 2015 STCRASH affected its domestic asset markets by analyzing generalized impulse response functions developed by Pesaran and Shin (1998). They account for the historical patterns of correlations among different shocks and are also invariant to the alternative orderings of the different markets. The effects of the shocks are formulated in terms of intensity, time-space, and direction of the responses of the variables in the VAR model, which can be expressed as:

$$\Delta Y_t = \alpha + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + \varepsilon_t \tag{15}$$

where:
$Y_t = Y_{1t}, Y_{2t}, \dots, Y_{kt}$ = I(1) Endogenous Variables
β_i = Matrix with coefficients associated with lag i
α = Vectors with coefficients associated with the intercepts
ε_t = Vector with impulses

5. Empirical results

5.1. Preliminary evidence

From the multivariate AR (1)-VECH-MGARCH model, Figure 1 presents the CV graphs [9]. Average daily CV value ranges from 0.00011% (bond) to 0.069% (public real estate). Additionally,

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[9]As the full results from the five-asset AR (1)-VECH-MARCH model is not the focus of this study, we do not report the results for brevity reason. Overall, we find that that the estimated variance coefficients for the conditional variance–covariance equation effectively captures the volatility and cross-volatility spillover across the five asset markets. We then extract five CV series for implementing the volatility spillover-connectedness analysis.

the Chinese stock market displays the highest risk spike around the mid-2015 stock market crash, with bond and commodity futures less hit by the crash[10].
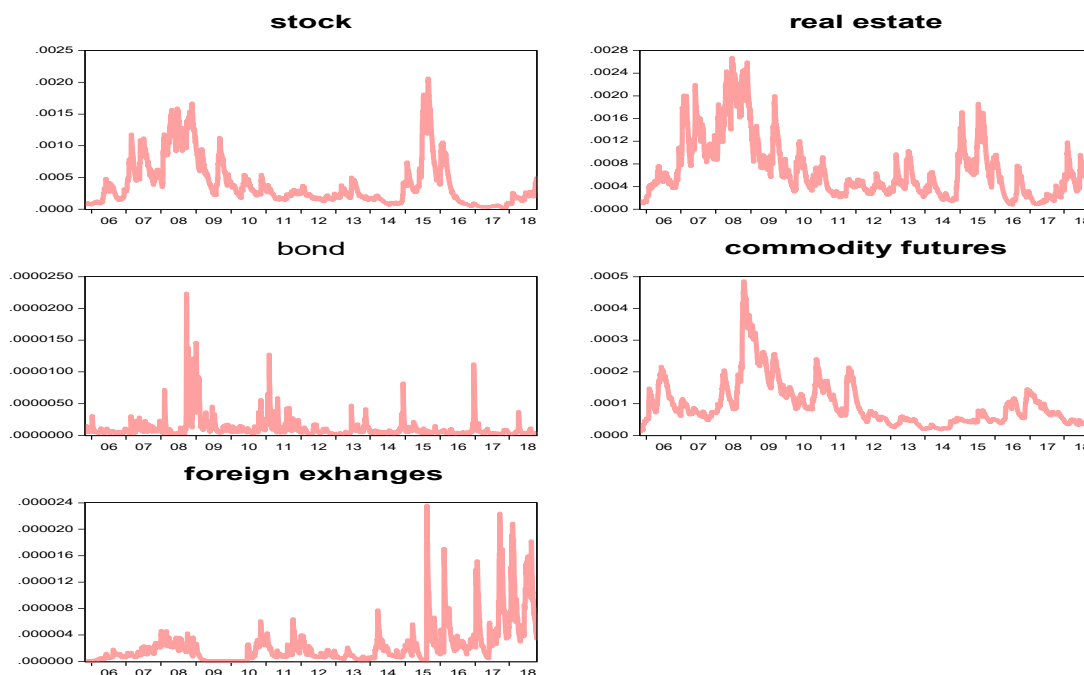

Figure 1. Conditional volatilities of China asset markets: November 1, 2005 to October 26, 2018.

Note: conditional volatilities are extracted from multivariate AR (1)-VECH-GARCH model.

5.2. Conditional volatility spillover-connectedness for the full study period

Table 2 presents the volatility spillover-connectedness index estimation based on ten days- ahead forecast error decomposition for the five-asset model over the full study period. According to this table, the average full-period volatility spillover-connectedness index, given in the lower right corner of the table, is approximately 16.3 percent implying on average, within the China economy, the five asset classes are not strongly volatility connected. The only largest cross-volatility coefficient is only 35.9 percent which indicates the highest volatility connectedness exists between real estate and stock. This weak cross-asset volatility linkage effect could be reasonably expected as China was largely isolated from the other large economies until 2006/2007. Additionally, there is a moderate to a high degree of own-volatility connectedness shown by the respective diagonal numbers.

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[10]China's Shanghai and Shenzhen stock exchanges peaked in June 2015. However, the two exchanges lost well over USD three trillion in market capitalization by July 2015-close to 1/3 China's GDP—as their indexes fell 32% and 40% respectively (Source: Special briefing, "China's stock market crash", July 2015, dun&bradstreet).

Table 2. Conditional volatility spillover-connectedness for Chinese stock, real estate, bond, commodity futures and foreign exchange markets from Nov1, 2005 to October 26, 2018.

	ST	RE	BO	CO	FX	
ST	62.3	35.9	0.1	1.7	0	
RE	34.5	64.5	0.1	0.9	0	
BO	0	0.1	99.6	0.3	0	
CO	2.9	1.8	3.2	92.1	0	
FX	0	0	0.1	0	99.9	
TO others	37	38	4	3	0	
FROM others	38	36	0	8	0	
NET contribution	−1	2	4	−5	0	
TOTAL contribution	100	102	103	95	100	**16.30%**

Notes: The values are estimated from the forecast error variance decomposition based on 10-day-ahead-forecasts and optimal lag length of VAR (1) as determined by SC.

Next, we present a rolling version of the total volatility connectedness index in Figure 2 to understand how the crisis shock affects the spillover transmissions and volatility connectedness across the five asset markets. The index was estimated from the 260-day rolling window estimation with a forecast horizon of 10-day and VAR lag order of 1 based on BIC.[11] The first window estimation is for the 260-day sample ending November 27, 2006, and the final one has an ending date of October 26, 2018. The average index is about 21.74 percent and fluctuates between 6.77 percent and 80.03 percent over the full period.[12]

Another notable feature of the plot is that larger variability in the detected volatility connectedness was responsive to global financial/economic events and domestic news announcements as indicated by at least two major and several minor connectedness spikes. The first major spike, which happened around June 2, 2010 was mainly in response to the GFC/EDC where the China government pegged the renminbi to the US dollar from August 2008 to June 2010. On June 19, 2010, the China government announced that it would increase its currency flexibility. Since then, the renminbi has appreciated. With the band of fluctuation increased, the volatility of the FX market significantly increased and consequently caused the sudden spike in the total volatility connectedness during June 2010.

The second major spike of the total connectedness index around December 16, 2016 was attributed to bond market volatility. With the US federal reserve increased the target interest rate since early December 2016, this tightening interest rate policy spurred capital outflow pressure on the China bond market yield spikes. For example, the 5- and 10-year government bond yields have soared by around 70 basis points since the end of October 2016. The corporate bond yield has also significantly risen, making it more difficult for domestic firms to pay their bondholders. During 2016, the number of corporate bond defaults was above two times larger than in 2015.

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[11]As a robustness check, we repeated the estimation for different rolling windows (100 days, 200 days and 300 days), different lag order up to 3 lags, and forecast horizons(10 days, 20 days, and 30 days). The results were insensitive to the choice of the rolling window sizes. For the brevity of the paper, we do not report the results with other sets of parameters. They will be provided upon request, wever, the author will provide the results once requested.

Finally, several other minor jumps in the total volatility connectedness were associated with the GFC/EDC events from 2007–2009 and from 2010–2011, as well as with the domestic stock market instability/crash from 2013 to 2016.
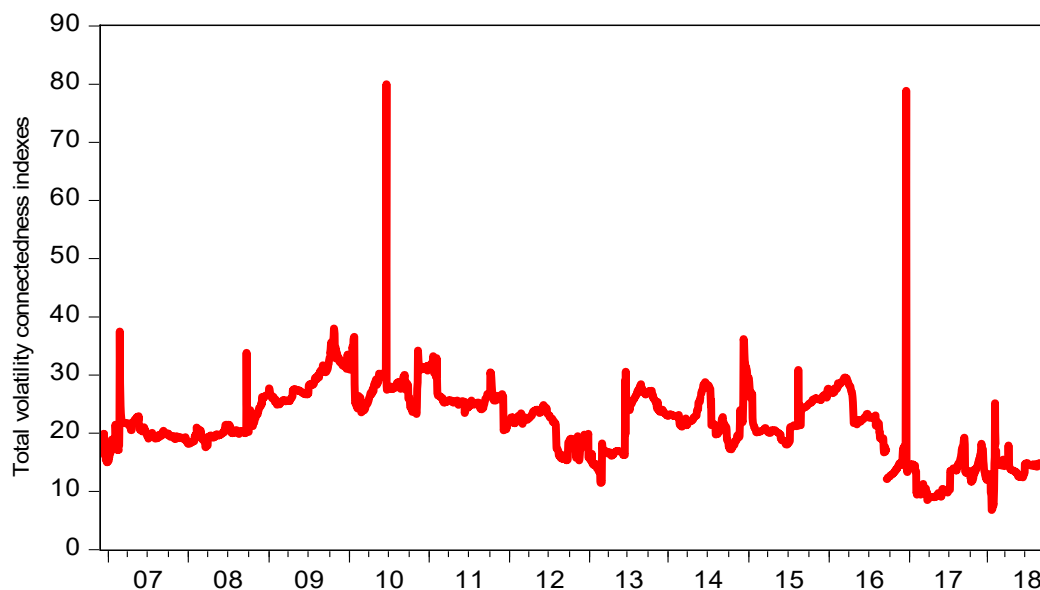

Figure 2. Dynamic total volatility connectedness index plot for China's stock, real estate, bond, commodity futures and foreign exchange markets.

Notes: The total volatility connectedness values (y-axis) are estimated from the forecast error variance decomposition based on 10-day-ahead-forecasts and optimal lag length of VAR (1) as determined by SC. The x-axis stands for the ending date of 260-day windows.

To identify which is the most influential financial market that contributed to the detected volatility spillover-connectedness, the full sample gross total, and net total volatility directional connectedness index values were evaluated, with the net index values displayed in Figure 3. On average, the largest gross transmission connectedness index to other markets is from the public real estate (38.99), followed by stock (37.14), bond (15.14), commodity futures (9.13), and currency (8.30). In contrast, with the largest gross connectedness index value from other markets to stock (41.98), followed by public real estate (35.65), commodity futures (15.67), currency (8.76), and bond (6.60). Consequently, Table 3 indicates that (a) the bond market is the top "transmitter" or "sender" of volatility spillover-connectedness in 70.2 percent of the time (with 2025 positive net index value) and (b) the commodity futures market is the top "recipient" or "giver" of volatility spillover-connectedness in 76.1 percent of the time (with 2195 negative net index value). [13] Overall, our results have highlighted the diversity of spillover transmission and volatility connectedness of the five financial markets over different periods.

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[13] The total number of the rolling net connectedness index observations is 2884.
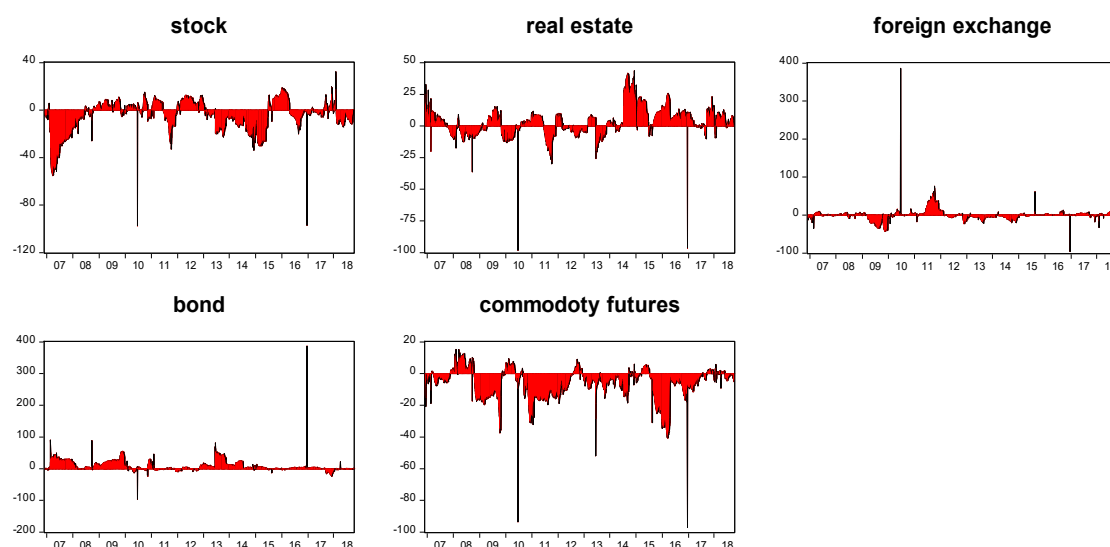
Figure 3. Dynamic net total volatility connectedness for China's stock, real estate, bond, commodity futures and foreign exchange markets.

Notes: Positive value indicates the asset market is a volatility connectedness sender (transmitter); negative value indicates the market is a volatility connectedness giver (absorber). The NTRCIs (y-axis) are estimated from the forecast error variance decomposition based on 10-day-ahead-forecasts and optimal lag length of VAR (1) as determined by SC. The x-axis stands for the ending date of 260-day windows.

Table 3. Analysis of net total volatility connectedness index values (net value).

Financial market	Net value	Percentage of Positive net value	Percentage of negative net value
Panel A: Net senders (transmitters) of risk spillover-connectedness			
bond	8.54	70.18%	29.82%
real estate	3.342	60.37%	39.63%
Panel B: Net receivers (absorbers) of risk spillover- connectedness			
Foreign exchange	-0.488	49.97%	50.03%
stock	-4.845	39.18%	60.82%
commodity futures	-6.55	23.93%	76.07%

Notes: positive value indicates the asset market is a volatility spillover-connectedness sender (transmitter); negative value indicates the asset market is a volatility spillover-connectedness receiver (absorber). The dynamic NTRCI values (y-axis) are estimated from the forecast error variance decomposition based on 10-day-ahead-forecasts and optimal lag length of VAR (1) as determined by SC. The x-axis stands for the ending date of 260-day windows.

We proceed to quantify the contribution to volatility connectedness of the five financial markets in net terms by estimating the dynamic net pairwise volatility connectedness indexes between the ten pairs of markets. Results indicate that the stock market is the net recipient of volatility connectedness from the public real estate (−3.466), bond (−3.030), and foreign exchange markets (−0.120), but is the net transmitter to the commodity futures market (1.771). Moreover, the net pairwise connectedness index values between several pairs of the financial markets changed over time with positive and negative values and implied, for example, a "flight-to-quality" from stock to bond and a "flight-from-quality" in the opposite direction. The net pairwise index value between stocks and commodity futures

is 61.23 percent positive and indicates the commodity future markets were able to transfer and disperse volatility to the stock markets. In contrast, public real estate and stock markets are only mildly volatility connected with the largest (absolute) net index value of only 3.466. Other plots indicate real estate is the net recipient of information transmission from the bond market (−1.656) but the net senders of stock (3.466), commodity futures (1.240), and foreign exchange markets (0.292). Finally, the foreign exchange market is the net recipient of volatility connectedness from the bond (−1.646) and the real estate markets (−0.292); but is the net volatility connectedness sender of the commodity futures (1.333) and stock markets (0.120). The results have again highlighted the diverse volatility connectedness relationships across the China domestic financial markets studied.
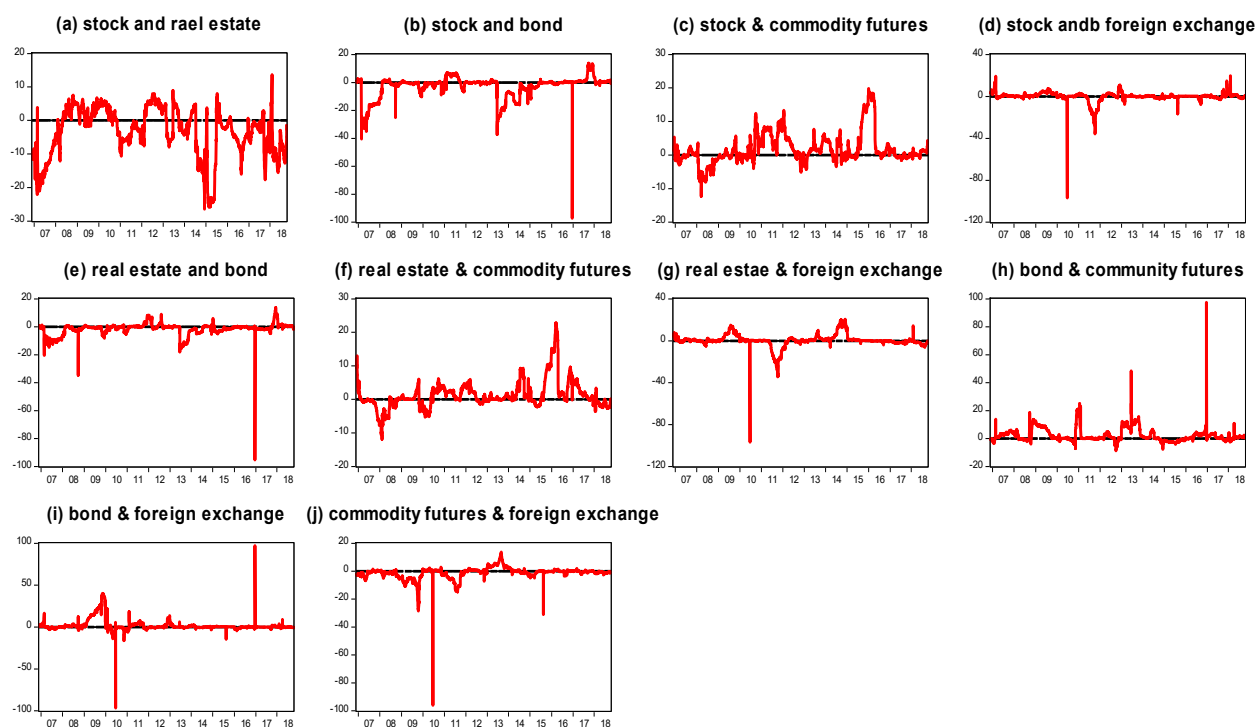

Figure 4. Dynamic net pairwise volatility connectedness index values for 10 pairs of asset markets.
Notes: Positive value indicates the 1st asset market is a volatility spillover-connectedness sender (transmitter); negative value indicates the 1st market is a volatility spillover-connectedness giver (absorber). The dynamic NPRCI values (y-axis) are estimated from the forecast error variance decomposition based on 10-day-ahead-forecasts and optimal lag length of VAR (1) as determined by SC. The x-axis stands for the ending date of 260-day windows.

5.3. Volatility connectedness during GFC, EDC, and STCRASH

A conclusion from the past literature is that the intensity of volatility connectedness in international/domestic financial markets is increasing during crisis episodes because markets tend to move together during financial turmoil periods. During crisis periods, financial markets' volatility interactions and inter/intra linkages can contribute to strong market connectedness that led to stronger volatility. Portfolio investors can thus find out if and how the crisis spill over to other domestic financial markets, as well as how sensitive which financial markets are to these crisis shocks. In this

section, we explore if and how the three crises (GFC, EDC, and STCRASH) spilled over to the Chinese five domestic financial markets and the impact on the net volatility spillover-connectedness shifts.

Based on the US Federal Reserve and other official timelines, the three crises are assigned with an appropriate time span as follow:

(a) GFC: August 2, 2007–November 4, 2009
(b) EDC: November 5, 2009–May 9, 2012
(c) STCRASH: June 12, 2015–January 7, 2016

Among the three crises, the domestic volatility spillover-connectedness impact of the STCRASH is insufficiently known. According to a report,[14] the value of shares in both China's main stock exchanges reached a peak on June 12 2015, then fell severely, with the Shanghai Composite Index and the Shenzhen Composite Index losing 32 and 40 percent of their stock values, respectively. This wiped out USD3 trillion in share value since mid-June (Washington Post). The crash followed a year-long stock market boom. Whilst there were several issues of concern put forward to explain this crash and commentators were divided over the effect the China STCRASH would have on the wider economy, one likely commercial implication is that China's bid to have the Yuan acknowledged as a reserve currency by the IMF in 2016 will be damaged by the failure to maintain a liquid stock market and lower volatility in financial inflows (dun&bradstreet, July 2015).

Nevertheless, the Chinese stock markets have shown signs of recovery amid significant intervention by the Chinese Government to stabilize the markets. Over 9–13 July 2015, this saw the Shanghai and Shenzhen Composite Index finished up from 2.4 percent to 10.9 percent. However, on January 4, 2016, the Shanghai and Shenzhen stock markets fell rapidly. The story repeated itself just two days later. On January 7, when trading on the Shanghai stock exchange was shut down for the day only 30 minutes after opening, resulting in the shortest day in the stock market history (US-China Economic and Security Review Commission, Issue Brief, January 14, 2016).

Liow (2015a) finds that the volatility connectedness shocks were pronounced among the developed financial markets examined during the GFC and EDC. In the present context, we examine to what extent this hypothesis will hold for domestic volatility connectedness and the consequent crisis impact on the financial market dependence. Towards this end, we run the following regression to explore the crisis impact on (i) the total volatility spillover-connectedness index and (b) the gross total transmission ratio for each financial market [15]:

Spillover transmission − connectedness* (*total or gross total*) $_t$= *f (constant, spillovers $_{t-1,}$ GFC dummy, EDC dummy, STCRASH Dummy)

For each asset class, the three dummy variables on GFC, EDC, and STCRASH take the value of one during the period of the respective crises and zero otherwise. The regressions are estimated with robust standard errors and adjusted for the one-lag autocorrelation effect.

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[14]Samuel white, "China's stock market crash", LIF 2015/0022, 16 July 2015.

[15]The gross total volatility transmission ratio is equivalent to the net total volatility connectedness index measure. This is because while the former expresses the transmission/connectedness profile of an asset class (relative to other asset classes in a system) in relative term using ratio, the latter expresses it in difference term. A gross volatility transmission ratio of more than one for an asset class indicates the asset class has a positive net total directional volatility spillover-connectedness index. Consequently, this asset class is a volatility transmitter relative to other asset classes in the system.

Table 4 indicates the regression estimates on the hypothesis that the respective spillover transmission-connectedness index/ratio underwent a positive and significant increase (up to 10 percent confidence level) during the three crisis periods. Specifically, the dummy variables corresponding to the three crises are positive and statistically significant in 3 cases (GFC), 4 cases (EDC), and 3 cases (STCRASH), respectively. These results have indicated that during the respective crisis times, some financial markets' volatility connectedness index values are quite sensitive to financial contagion. It further appears that the stock and bond markets were consistently impacted by the three crises. In contrast, the commodity futures market was least affected by the adverse effects of the three crises due to its risk hedging quality displayed during high volatility periods. Our results thus indicate that the role of volatility connectedness increased during the three financial crises and provide valuable inputs for regulators and policymakers to devise coordinated rules and policies to minimize the shifted connectedness shock effects and to facilitate continuing growth of various domestic asset markets within the economy. Finally, the increase in volatility connectedness during the crisis periods implies that mixed-asset portfolio diversification may yield little benefit to the investors. Our findings are broadly consistent with the crisis return connectedness findings between the US stock and housing markets (Tsai, 2015).

Table 4. Tests of crisis impact on volatility spillover-connectedness index/ratio.

Dependent variable	Coefficients for explanatory variables				
	constant	lagged (−1)	GFC	EDC	CSTCRASH
Total spillover−connectedness index	2.120*	0.888***	**0.516***	**0.867***	**0.598***
Gross transmission (Stock)	0.019***	0.977***	**0.004***	**0.005***	**0.014***
Gross transmission (Real estate)	0.030***	0.976***	−0.003	−0.007**	−0.002
Gross transmission (Bond)	1.727**	0.560**	**0.004***	**0.005***	**0.014**
Gross transmisson (Commodity futures)	0.052***	0.941***	0.012	−0.015	−0.015
Gross transmission (Foreign exchange)	0.890***	0.312**	−0.053	**0.993***	0.613

Note: This table is based on following regression model:

Spillover transmission − connectedness (total or gross total) $_t$ = f (constant, spillovers $_{t-1}$, GFC dummy, EDC dummy, STCRASH Dummy). Standard errors follow a robust procedure for estimating a covariance matrix corrected by heteroscedasticity and autocorrelation (Newey and West, 1987). The spillover/gross transmission estimates are derived using a forecast horizon of 10 days and a rolling window size of 260 days. Highlighted yellow are significant (10 percent or less) dummy coefficients. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent levels, respectively.

5.4. Causal dependence during three crises: linear and nonlinear causality

Since causal links may contribute to volatility connectedness and market dependence, we next evaluate the linear and nonlinear causal dependence between a pair of China's financial markets' conditional volatilities (CVs) during the three financial crisis periods. Evidence from this causality analysis may further indicate the relative influence of the five financial markets in contributing to the financial market dependence.

Table 5 reports the causality results. The linear regression results indicate the presence of bidirectional (feedback) relationships between bonds and commodity futures, as well as between commodity futures and foreign exchanges during the GFC; between bonds and commodity futures during the EDC, as well as between real estate and commodity futures during the STCRASH, at the conventional statistical level. Moreover, there is evidence of four (GFC), three (EDC), and one (STCRASH) significant one-way directional causal links, running across the various asset markets, implying four out of the five asset classes

(commodity futures, bonds, foreign exchanges, and real estate were not isolated from each other and were instead linearly causal interactive during the respective crisis periods.

Table 5. Linear and Nonlinear Granger causality tests on conditional volatilities (CV) of China's five asset markets during the three crisis periods.

Direction		Linear		Nonlinear	
	Lag	L => R(fval)	R => L(fval)	L => R(tval)	R =>L (tval)
Panel A. GFC					
ST<=>RE	1	4.817**	0.067	1.723**	0.085
ST<=>BO	2	0.859	2.689*	1.222	−0.284
ST<=>CO	1	0.74	0	1.81**	1.095
ST<=>FX	1	1.648	2.435	1.18	1.68**
RE<=>BO	2	0.63	1.845	1.102	0.428
RE<=>CO	1	1.686	0.091	0.855	0.819
RE<=>FX	1	2.768*	1.378	−0.202	0.41
BO<=>CO	3	5.881***	14.605***	1.635*	3.666***
BO<=>FX	2	3.025**	0.045	1.049	−1.329
CO<=>FX	1	4.068**	12.239***	−0.141	−0.161
Panel B. EDC					
ST<=>RE	1	0.014	2.209	1.659**	0.21
ST<=>BO	1	0.293	4.726**	0.994	0.483
ST<=>CO	1	0.373	0.01	1.775**	0.128
ST<=>FX	1	1.072	3.06*	−0.394	−0.133
RE<=>BO	1	0.155	0.115	0.495	1.321*
RE<=>CO	1	0.413	0.005	−0.399	−0.625
RE<=>FX	1	1.205	1.297	0.396	0.943
BO<=>CO	1	4.687**	3.601*	0.852	0.948
BO<=>FX	1	1.288	7.64***	0.188	1.393*
CO<=>FX	1	0.955	2.142	0.917	−0.572
Panel C. STCRASH					
ST<=>RE	1	0.526	1.496	1.454*	−1.638*
ST<=>BO	2	1.78	0.242	0.992	−0.243
ST<=>CO	1	7.501***	1.557	1.314*	0.939
ST<=>FX	1	0.32	0.181	−1.733**	−1.518*
RE<=>BO	1	0.009	0.743	1.088	−2.448***
RE<=>CO	1	14.737***	3.953**	1.431*	1.938**
RE<=>FX	1	0.483	0.047	−1.821**	−1.577*
BO<=>CO	1	0.006	0.548	0.233	0.446
BO<=>FX	2	0.407	0.613	1.205	−0.951
O<=>FX	1	0.022	0.8	−1.581*	0.974

Notes: This table presents the results of Granger causality tests for three crisis subsample periods: GFC (Panel A), EDC (Panel B), and STCRASH (Panel C). Each panel shows the F-statistics of linear causality tests and t-statistics of nonlinear causality test based on Diks and Panchenko (2006). The bandwidth (epsilon) is set to 1 for nonlinear causality test. The direction of significant (at least at the 10 percent level) causality is recognised by three types of colour-shading as follow: Red: unidirectional from left (1st asset) to right (2nd asset); green: unidirectional from right (2nd asset) to left (1st asset); Blue: bidirectional. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent test levels, respectively. The five asset classes are: stock (st), public real estate (re), bond (bo), commodity futures (co) and foreign exchange (fx)).

For the nonlinear DP test, its most striking feature is that there are rich causal interactions between the five financial markets during the stock market crash period. Specifically, we find evidence of a significant bidirectional causal dependence in four pairs of financial markets (stocks and real estate, stocks and foreign exchanges, real estate and commodity futures, real estate and foreign exchanges) and another three pairs of significant unidirectional causal links running from stocks to commodity futures, from bonds to real estate as well as from commodity futures to foreign exchanges. These results reinforce the idea that all the five financial markets within the China economy were not sparred by the domestic crisis, which may affect the market causal dependence differently between the financial markets (i.e., bidirectional, unidirectional, and independence).

In summary, in the context that the nonlinear Granger causality tests generally have higher power against linear relationships, our CV analysis adequately supports a nonlinear Granger modeling of the markets' causal dependence. One possible implication is that the five domestic markets influenced and have been influenced through their linear and nonlinear causal links between the respective CVs. Consequently, modeling the connectedness dynamics should be none within a nonlinear VAR system in the addition of only through linear regression.

5.5. Generalized impulse response function analysis

Finally, impulse response function analysis aims to generate additional insights into the transmitting mechanisms of the five markets' movements. By graphically displaying the expected response of each variable to shocks in the variable and other variables in the system, we observe the relative speed of adjustment of the variables in the VAR system. In the current study, we appeal to the generalized impulse response function (GIRF) developed by Pesaran and Shih (1998) such that the findings are invariant to the ordering of the variables in the system.

We analyze the patterns of the dynamic response for each of the five markets to a shock, i.e., the positive residuals of one standard deviation unit in a financial market are examined. Figure 5 provides five plots of time paths of the impulse response to a domestic shock in stocks, real estate, bonds, commodity futures, and foreign exchanges during the STCRASH[16]. The days after the impulse shocks are shown on the horizontal axis, with the vertical axis measures the magnitude of the response whose scale is that 1.0 is equal to one standard deviation.

Beginning with the GIRF of the Chinese stock market, we observe volatility shocks to real estate initially leads to a steeper positive decline in the real estate market for the first 1–2 days and eventually flattens out after 3 days. For the real estate GIRF, shocks to stocks begin with a similar declining effect in the 2–3 days and then flattens out thereafter. We also observe that the GIRFs for the China real estate market are similar to the GIRFs for the Chinese stock market, implying that investment in these two markets is close substitutes during this period.

In the GIRF for China bonds, shocks to stocks, real estate, and foreign exchanges begin with negative values and then proceed with increasing positive effects till flattening out after 2–4 days. In contrast, shocks

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[16]We only conducted GIRF during the STCRASH since this analysis has received insufficient attention during the period.

to community futures are associated with an almost flattened response from the GIRF for bonds. In the GIRF for commodity futures, shocks to stocks, real estate, and commodity futures begin with a positive effect and then decline steeply after 2–3 days to flatten out. In contrast, bonds and foreign exchanges appear to be rather insensitive to shocks in commodity futures. Finally, the GIRF for the China foreign exchange market generates different response patterns. Whilst stocks and real estate start immediately with a positive but steep declining trend for two days and then recover the losses until they flatten out after five days, the commodity futures and bond markets receive the shocks with a relatively flattened response.

In summary, we may conclude that during the STCRASH period, stocks and real estate tend to react with similar and steeper positive or negative responses to shocks. In contrast, China bonds and commodity futures markets appear to have milder levels of shocks response and fluctuate with fewer magnitudes over time. Overall, the relative speed of adjustment of the five financial markets to shocks in the VAR system appears to be fast.
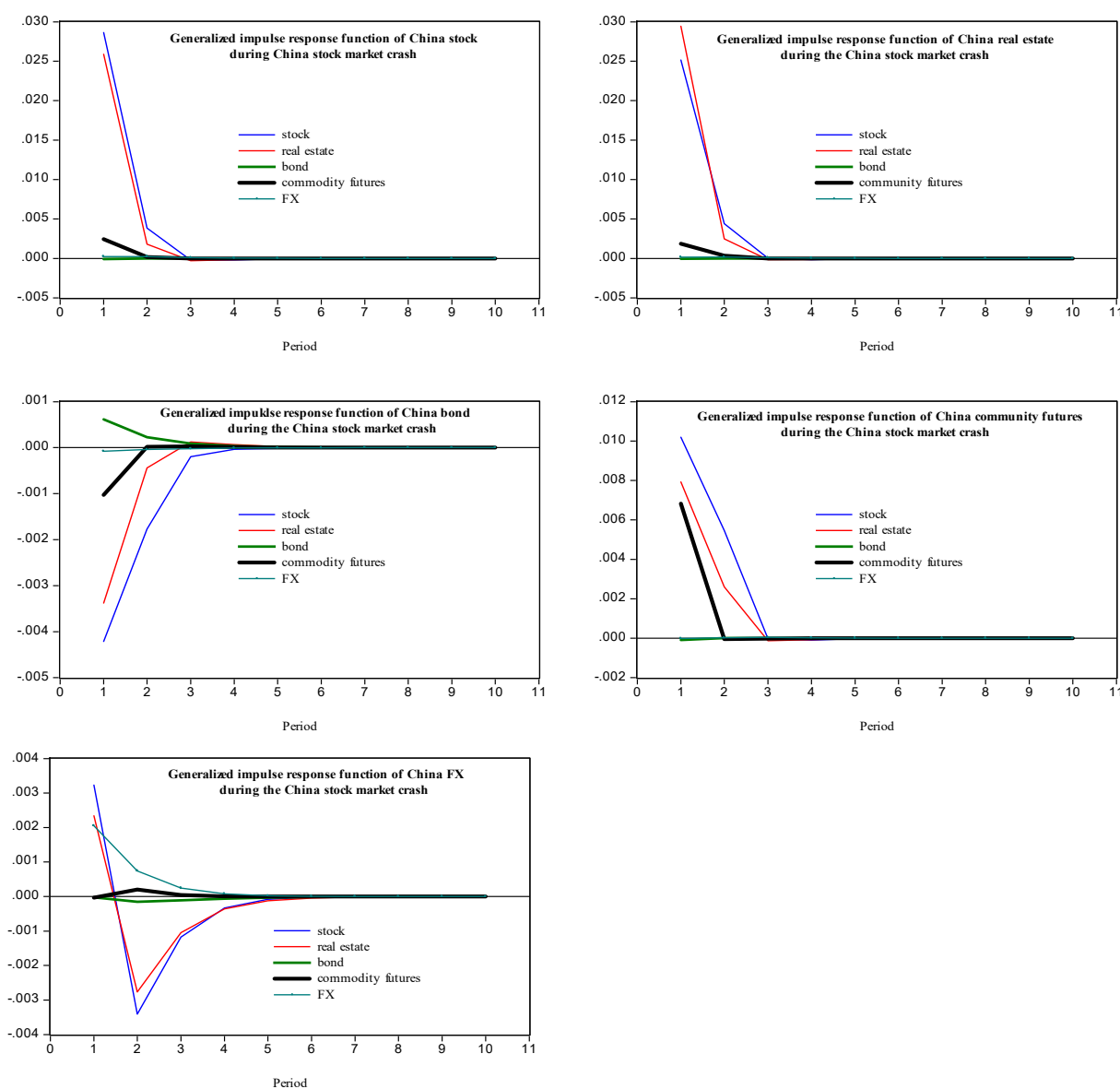

Figure 5. Generalized impulse response function (GIRF) for China 5-asset markets: 10-day forecast horizon.

6.   Summary and conclusions

Although there are growing studies investigating financial market relationships in the domestic economy, insufficient attention was given to an examination of the dynamics of volatility connectedness and financial market dependence within the increasingly open and growing China. In this research, we have studied such dynamics among the Chinese five major financial markets: stock, public real estate, bond, commodity futures, and foreign exchange during the full period from Nov 2005 to Oct 2018, as well as during the three crisis periods: GFC, EDC, and 2015 STCRASH. We include public real estate in this study to reflect the increasingly important role of this new "asset" class in the China economy and financial markets. This is another new feature of the study that adds to the volatility connectedness and domestic asset market dependence literature in an emerging economy context.

This study produces five main conclusions:

(a) The five Chinese major domestic financial markets are not strongly connected since on average, only between 16.30 and 21.74 percent of the forecast error variances are due to the volatility connectedness shocks among the markets. One important implication is that most volatility connectedness shocks are idiosyncratic, and the cross-market connection is generally less frequent in this closed economy before the 1980s.

(b) Over the full study period, the bond market is the predominant market of information transmissions because the net spillover-connectedness in this market is greater than that in the stock, real estate, commodity futures, and foreign exchange markets. This is followed by the real estate market, which is ranked No.2 shocks "sender". In contrast, the commodity futures, stock, and foreign exchange markets are the net "recipients" of volatility connectedness shocks.

(c) The role of net shocks sender and net shocks recipient shifts between "stable" and "crisis" times, implying less similar cross-market relationships and crisis contagion are undergoing in a growing economy. During the STCRASH period, the stock market acted as a net volatility sender instead of taking the role of a volatility net receiver during the full period.

(d) The five China financial markets influenced and have been influenced through their linear and nonlinear causal volatility dependence during the three crisis periods. Moreover, the nonlinear causal dependence appears to be very strong among the markets during the stock market crash, implying that the five markets could be more causally interactive during an internal financial crisis rather than influenced by an external crisis.

(e) During the STCRASH period, stock and public real estate reacted with similar and steeper positive or negative responses to shocks. In contrast, bond and commodity futures appear to have milder levels of shock response and fluctuate with less magnitude over time.

(f) Our study has adequately highlighted the significant role of the public real estate market played in the China economy, especially during the domestic crisis periods.

Overall, our findings are probably useful to many governments and market regulators who are searching for effective solutions to manage the domestic transmission of volatility connectedness shocks and to promote further financial market development within the economy. However, there could be several limitations that are out of scope in this study. First, we do not disentangle the underlying mechanisms that derive the spillover system. The connectedness findings across the domestic financial markets should gain comprehensive insights by further analyzing the main factors that affect the information transmission among the five financial markets on bivariate and multivariate

basis in accordance with changing market conditions. In addition, there could be other empirical methods that might capture different characteristics of the spillover system. Thus, future extension can also include a combined statistical time-frequency volatility connectedness analysis, network approach, and macroeconomic perspective to understand the market dependence and portfolio diversification implications of return and volatility connectedness during the normal and crisis periods in an emerging market context.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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