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Who are the net senders and recipients of volatility spillovers in China's financial markets?

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ABSTRACT

Using a spillover index approach, we investigate volatility spillovers across China's stock, bond, commodity futures, and foreign exchange (FX) markets and their evolution during the period 2005–2015. We find that these four financial markets are weakly integrated. The stock market is the largest net sender of volatility spillovers to other markets, followed by the bond market, and the FX and commodity futures markets are net recipients. The time-varying volatility spillovers show that the recent global financial crisis and the European sovereign debt crisis strongly influenced China's financial markets.

1. Introduction

During the past three decades the Chinese economy has rapidly expanded and its financial markets have played an important role in the development of its real economy. Through such practices as the non-tradable shares reform, the introduction of stock index futures, and the opening of the Small and Medium-sized Enterprise (SME) board and the Growth Enterprise Market (GEM), China's stock market, launched in 1990, has become the world's second largest capital market with a market capitalization of USD 10.3 trillion in June 2015. China's bond market has grown from virtual nonexistence to the third largest in the world with a volume of approximately Renminbi (RMB) 44.85 trillion (USD 6.91 trillion) at the end of 2015. In 2009 China's commodity futures market became the world's largest, and in 2014 the trading contracts reached 2.29 billion. By liberalizing the RMB exchange rate regime from a pegged exchange rate to a managed float exchange rate with reference to a basket of currencies, China's foreign exchange (FX) market has become more influential worldwide and the RMB has the possibility of becoming a new strong world currency, e.g., on 1 October 2016 RMB will be included in the Special Drawing Right (SDR) with a 10.92% weighting.

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The volatilities of different asset prices can strongly influence each other, an effect known as volatility spillover. Understanding volatility spillovers between prices of different financial entities is crucial in the development of trading and hedging strategies and in formulating regulatory policies. The goal is to be able to predict which financial market will spill over to which and when. Although volatility spillovers in China's financial markets have received much study, most research has focused on volatility spillovers within the same type of financial market or between two types of financial market, e.g., segmented stock markets (A-share and B-share markets) (Weber and Zhang, 2012), stock and bond markets (Li and Zou, 2008), and stock and FX markets (Zhao, 2010; Aftab et al., 2015), but volatility spillovers among four important markets in China—the stock, bond, commodity futures, and FX markets—have received little attention. Thus our goal here is to investigate volatility spillovers among these four markets[1] and to understand their dynamic behavior.

Using the spillover index approach proposed by Diebold and Yilmaz (2009; 2012), we study volatility spillovers among the four markets. We both investigate total volatility spillovers across the four markets and examine the directional volatility spillovers from or to a particular market. We also analyze the net volatility spillovers of each market and between each pair of markets to determine which markets in China are net senders and which are net recipients of the volatility spillovers. Understanding which markets are the net senders and recipients of volatility spillovers in China is essential when managing asset risk, assessing market stability, and formulating regulatory policies. Investors usually benefit from a diversified portfolio of assets (e.g., stocks, bonds, commodity futures, and FX) when the assets are not well correlated. When investors face financial and macroeconomic uncertainty, for example, information about net senders and net recipients of volatility spillovers is useful in predicting the potential risk of a diversified portfolio and helps investors make timely adjustments to their asset portfolio and greatly improves their investment and hedging decisions. To monitor the market stability and maintain the market's effective operations, policy-makers need to understand how the frequency and direction of volatility spillovers among major financial markets will respond to financial and macroeconomic uncertainty. When policy-makers are able to distinguish net senders from net recipients of volatility spillovers under different economic conditions, they can more accurately formulate effective policies for influencing the markets and thus achieve the desirable intensity and direction of volatility spillovers across major financial markets.

2. Methodology

The spillover index approach developed by Diebold and Yilmaz (2009; 2012)[2] builds on vector autoregressive (VAR) models but focuses on variance decomposition, which is widely used to quantify volatility spillovers between different financial markets (e.g., Diebold and Yilmaz, 2014; Lucey et al., 2014; Batten et al., 2015; Yarovaya et al., 2016a; 2016b).

Consider a covariance stationary N-variable VAR(p) model, $Y_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim$ i.i.d.$(0, \Sigma)$ is an $N \times 1$ vector of disturbances. The VAR model can be transformed into a moving average (MA) representation, $Y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, where the $N \times N$ coefficient matrices A_j are recursively defined as $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \ldots + \Phi_p A_{j-p}$, A_0 is an identity matrix, and $A_j=0$ for $j < 0$.

Using the generalized VAR (GVAR) framework, Diebold and Yilmaz (2012) defines *own variance shares* as the fraction of the H-step-ahead error variance in predicting Y_i due to shocks to Y_i, and *cross variance shares* (or *spillovers*) as the fraction of the H-step-ahead error variance in predicting Y_i due to shocks to Y_j, where $i, j = 1, 2, \ldots, N$ and $i \neq j$. The H-step-ahead forecast error variance decomposition and its normalization are respectively defined

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

and

$$\tilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)}, \tag{2}$$

where Σ is the variance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term for the j-th equation, e_i is a selection vector with one as element i and zero otherwise, $\sum_{j=1}^{N} \tilde{\phi}_{ij}(H) = 1$, and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H) = N$.

Using the volatility contributions from the GVAR variance decomposition, the total volatility spillover (TVS) index is defined

$$\mathrm{TVS}(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \cdot 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij}(H)}{N} \cdot 100, \tag{3}$$

which is used to quantify the contribution of the volatility shock spillovers across various financial markets to the total forecast error variance (Diebold and Yilmaz, 2012).

Similarly, directional volatility spillovers (DVS) are used to measure volatility spillovers received by market i from all other markets j and the reverse direction of transmission from market i to all other markets j, which are respectively given

[1] Because China's interest rate is not yet fully liberalized, we do not consider the money market in our study.

[2] Note that Klößner and Wagner (2014) use Diebold and Yilmaz (2009) to develop a new, faster algorithm for calculating robust spillover values.

Table 1
Descriptive statistics of volatilities for China's stock, bond, commodity futures (CF), and FX markets from 5 January 2005 to 31 December 2015.

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	ADF
Stock	0.0133	0.0133	2.0589	8.8508	5694.687***	−8.9151***
Bond	0.0005	0.0006	4.0357	35.6264	125671.1***	−9.3777***
CF	0.0066	0.0063	1.9692	8.2264	4764.317***	−8.8279***
FX	0.0019	0.0019	2.9178	19.9208	35640.89***	−14.8897***

Notes: The Jarque–Bera statistic tests for the null hypothesis of Gaussian distribution. The ADF statistic denotes the Augmented Dickey–Fuller test for a unit root. The null hypothesis of ADF test is a unit root in the sample volatilities. *** denotes the rejection of null hypothesis at the 1% significance level.

by

$$\mathrm{DVS}_{i\leftarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\phi}_{ij}(H)}\cdot 100 = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}_{ij}(H)}{N}\cdot 100 \tag{4}$$

and

$$\mathrm{DVS}_{i\rightarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}_{ji}(H)}{\sum_{i,j=1}^{N}\tilde{\phi}_{ji}(H)}\cdot 100 = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}_{ji}(H)}{N}\cdot 100. \tag{5}$$

The net volatility spillover (NVS) from market i to all other markets j is defined as the difference between Eqs. (4) and (5), i.e.

$$\mathrm{NVS}_i(H) = \mathrm{DVS}_{i\rightarrow j}(H) - \mathrm{DVS}_{i\leftarrow j}(H). \tag{6}$$

In a similar way, the net pairwise volatility spillover (NPVS) between markets i and j is defined

$$\begin{aligned}\mathrm{NPVS_{ij}(H)} &= \left(\frac{\tilde{\phi}_{\mathrm{ji}}(\mathrm{H})}{\sum_{\mathrm{i,k=1}}^{\mathrm{N}}\tilde{\phi}_{\mathrm{ik}}(\mathrm{H})} - \frac{\tilde{\phi}_{\mathrm{ij}}(\mathrm{H})}{\sum_{\mathrm{j,k=1}}^{\mathrm{N}}\tilde{\phi}_{\mathrm{jk}}(\mathrm{H})}\right)\cdot 100\\ &= \left(\frac{\tilde{\phi}_{ji}(H)-\tilde{\phi}_{ij}(H)}{N}\right)\cdot 100.\end{aligned} \tag{7}$$

3. Data and empirical results

We select the China Securities Index (CSI) 300 index, CSI Aggregate Bond (AB) index, CSI Commodity Futures Composite (CFC) index, and RMB Real Effective Exchange Rate (REER) index as proxies for China's stock, bond, commodity futures, and FX markets, respectively.[3] We collect the daily closing values of each index from 4 January 2005 to 31 December 2015, a total of 2671 observations.[4] The data from the three CSI indices are retrieved from Wind Info. We select the RMB REER index to represent the FX market because it both takes into account currency changes in the fellow primary trade countries and considers the effects of inflation. We acquire the data of the RMB REER index from the website of the Fudan RMB Exchange Rate Index (http://ifsfd.fudan.edu.cn/fdurmb/).

Following Forsberg and Ghysels (2007) and Antonakakis and Kizys (2015), we define the asset volatility as the absolute return $V_t = |\ln P_t - \ln P_{t-1}|$, where P_t is the daily closing value of the financial index on day t.[5] Table 1 provides volatility statistics for the four financial markets. The stock market has the highest volatility, followed by the commodity futures, the FX, and the bond markets. The ADF unit root test shows that each set of volatilities is stationary, indicating that they can be used in the VAR analysis.

[3] The CSI 300 index, which is composed of the largest 300 A-shares listed on Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) and covers more than 60% of market capitalization, reflects the price fluctuation and performance of China's stock market. The CSI AB index consists of government bonds, financial bonds, and corporate bonds listed on SSE, SZSE, and the inter-bank market. The CSI CFC index comprises all of the commodity futures that have been listed for more than one year at three Chinese commodity futures exchanges, i.e., the Dalian Commodity Exchange, the Shanghai Futures Exchange, and the Zhengzhou Commodity Exchange.

[4] The beginning date of the sample is of interest because (i) the base date for both the CSI 300 and CFC indices launched by the CSI Co., Ltd. is 31 December 2004 and (ii) the two landmark events in China's financial markets occurred in 2005, i.e., the RMB exchange rate regime reform and the non-tradable shares reform were launched on 21 July 2005 and 5 September 2005, respectively.

[5] In the literature (e.g., Diebold and Yilmaz, 2012; Yarovaya et al., 2016a; 2016b), range volatility estimators are the widely used volatility measure for investigating the dynamic intensity of volatility spillovers across financial markets, but in our study we use the absolute return as a measure of volatility because (i) the daily opening, high, and low prices of the CSI AB and CFC indices and the RMB REER index are unavailable and thus range volatility estimators cannot be chosen, and (ii) the absolute return is one of the most popular academic definitions of volatility and can forecast volatility much better than other measures (Forsberg and Ghysels, 2007; Antonakakis and Kizys, 2015). For additional advantages of using absolute return as a measure of volatility see Forsberg and Ghysels (2007).

Table 2
Volatility spillover table for China's stock, bond, commodity futures (CF), and FX markets from 5 January 2005 to 31 December 2015.

	Stock	Bond	CF	FX	Contr. from others
Stock	98.722	0.392	0.612	0.275	1.278
Bond	0.130	98.141	0.942	0.786	1.859
CF	4.281	1.011	93.505	1.203	6.495
FX	0.867	2.940	1.651	94.542	5.458
Contr. to others	5.278	4.343	3.205	2.264	TVS index:
Contr. including own	104.000	102.484	96.710	96.806	15.090/400 = 3.773%
Net volatility spillover	4.000	2.484	−3.290	−3.194	

Notes: The values are calculated from variance decompositions based on 10-step-ahead forecasts. The optimal lag length for the VAR models is 3 determined by Bayesian Information Criterion.

Table 3
Break points in volatility for China's stock, bond, commodity futures (CF), and FX markets from 5 January 2005 to 31 December 2015.

Break	Stock	Bond	CF	FX
1	08/12/2006	01/09/2006	01/08/2008	31/08/2006
2	11/03/2009	29/08/2008	25/03/2010	05/08/2008
3	09/02/2012		02/12/2011	
4	19/05/2014			

Notes: The break points are determined by the sequential L+1 breaks vs. L method of Bai and Perron (1998; 2003). Parameters of the break test are set as follows: Trimming 15%, Maximum breaks 5, and Significant level 5%. Statistics of the break test use the HAC covariance estimation, including pre-whitening with lag one, Quadratic-Spectral kernel, and Andrews bandwidth. The break test allows heterogeneous error distributions across breaks. The date format is dd-mm-yyyy. The detailed estimates are available upon request.

We use the GVAR framework of Diebold and Yilmaz (2012) to calculate the total, directional, and net (pairwise) volatility spillovers, where the optimal lag length for the VAR models is determined by the Bayesian Information Criterion (BIC). Table 2 shows the volatility spillover estimates for the four markets over the entire period from 2005 to 2015. Note that most volatility shocks in markets are internal and that cross-market spillovers are infrequent, implying that China's financial markets are weakly integrated. The value of the total volatility spillover (TVS) index is only 3.773%, significantly lower than that of US financial markets (12.6%) reported by Diebold and Yilmaz (2012). Although volatility spillovers across markets are infrequent, we find (i) that spillovers from other markets to the stock market are indeed infrequent (only 1.278%), but that the stock market is the largest contributor of volatility spillovers to the other markets at 5.278%, (ii) that the commodity futures market receives the most volatility spillovers (most of them from the stock market) at 6.495% followed by the FX market at 5.458%, (iii) that the spillover contribution of the FX market to the other markets is the smallest (2.264%), suggesting that the FX market has relatively little influence in China, and (iv) that the net volatility spillovers of the stock and commodity futures markets are the largest and smallest, respectively.

To better understand how crisis shocks affect the volatility spillovers across China's financial markets, we check for robustness over the sample period by focusing on structural breaks in volatility. We use the multiple structural change models proposed by Bai and Perron (1998; 2003) to detect break points in volatility for each market.[6] Table 3 shows the break points in volatility for the four markets over the entire period. We detect four, two, three, and two break points in volatility for stock, bond, commodity futures, and FX markets, respectively, which suggests that a higher volatility market has more breaks points. Note that most of the break points occur in the 2008–2012 period, implying that the recent global financial crisis and the European sovereign debt crisis greatly influenced China's financial markets. Using the volatility break points in each market, we divide the sample period into subperiods before and after the break points. Due to space limitations, in Table 4 we only present estimates of the TVS index and net volatility spillover (NVS) for the four markets at different subperiods according to their break points. The values of the TVS index and NVS change across the subperiods. During the subperiods covering the global financial crisis and the European sovereign debt crisis, the TVS index and NVS have a higher absolute value, indicating that these crisis shocks increase the intensity of volatility spillovers in China's financial markets. From the NVS values shown in Table 4, we find (i) that the stock market is always the net sender of volatility spillovers, and the FX market is always the net recipient, and (ii) that the bond market is the net sender of volatility spillovers except for the subperiods prior to 2007, and the commodity futures market is the net recipient except for the subperiods prior to

[6] Other approaches can also be used to detect break points. For example, Yarovaya et al. (2016a) use the iterated cumulative sum of squares (ICSS) algorithm of Inclan and Tiao (1994) to explore multiple break points in stock market volatility, and Yarovaya and Lau (2016) employ the cointegration test with two unknown regime shifts proposed by Hatemi-J (2008) to detect possible break points in stock markets.

Table 4
Total volatility spillover (TVS) index and net volatility spillover for China's stock, bond, commodity futures (CF), and FX markets at different subperiods according to their break points.

Subperiod	TVS index	Net volatility spillover			
		Stock	Bond	CF	FX
Panel A: Subperiods determined by break points in volatility for the stock market					
05/01/2005–07/12/2006	2.274%	1.278	−1.420	1.114	−0.972
08/12/2006–10/03/2009	7.522%	1.944	10.618	−5.880	−6.682
11/03/2009–01/02/2012	4.777%	14.264	1.856	−12.740	−3.381
09/02/2012–16/05/2014	2.341%	0.806	2.126	−1.082	−1.850
19/05/2014–31/12/2015	2.763%	1.482	1.912	−2.869	−0.525
Panel B: Subperiods determined by break points in volatility for the bond market					
05/01/2005–31/08/2006	2.566%	1.902	−1.108	0.594	−1.388
01/09/2006–28/08/2008	3.104%	2.659	4.500	0.335	−7.494
29/08/2008–31/12/2015	5.550%	7.012	2.485	−6.706	−2.790
Panel C: Subperiods determined by break points in volatility for the CF market					
05/01/2005–31/07/2007	1.616%	1.730	0.338	0.641	−2.709
01/08/2008–24/03/2010	6.643%	11.023	5.946	−11.494	−5.475
25/03/2010–01/12/2011	5.583%	12.377	4.092	−13.750	−2.719
02/12/2011–31/12/2015	2.305%	2.008	2.016	−2.336	−1.688
Panel D: Subperiods determined by break points in volatility for the FX market					
05/01/2005–30/08/2006	2.551%	1.868	−1.096	0.600	−1.371
31/08/2006–04/08/2008	3.496%	1.782	6.450	1.188	−9.421
05/08/2008–31/12/2015	4.163%	7.385	4.124	−7.656	−3.852

Notes: This table shows the robustness check of volatility spillovers across China's stock, bond, commodity futures, and FX markets with break points. The detailed volatility spillover estimates are available upon request.

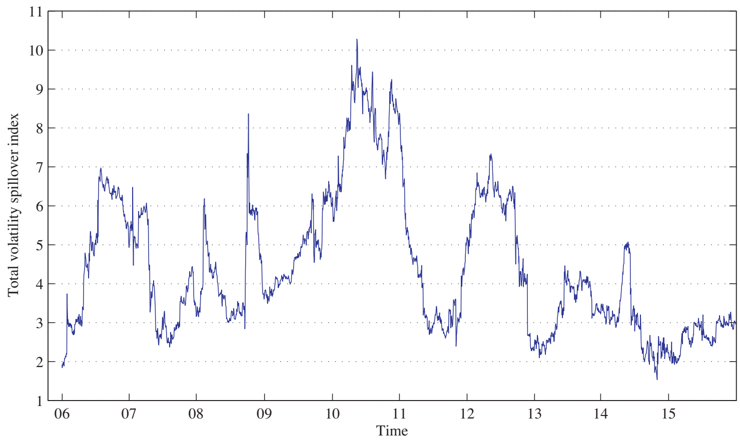

Fig. 1. Dynamic total volatility spillover index for China's stock, bond, commodity futures, and FX markets. Notes for this and below figures: The values are calculated from the forecast error variance decompositions on 10-step-ahead forecasts. The optimal lag length for the VAR models is dynamic determined by Bayesian Information Criterion. The time on the x-axis stands for the ending date of a 240-day window.

September 2008. There are exceptions for the bond and commodity futures markets because (i) prior to 2007 there were sound macro fundamentals, sound banks, and signs of financial exuberance in China (Filardo et al., 2010), which caused a "flight-from-quality" from the bond market to other markets (e.g., stock and commodity futures) and thus increased the net volatility spillovers from other markets to the bond market, and (ii) China's commodity futures market grew rapidly from January 2005 to September 2008 (e.g., the CSI CFC index grew 70% from 100 to over 170),[7] which explains the increase in net volatility spillovers from the commodity futures market to other markets.

We next investigate the dynamic features of volatility spillovers in China's financial markets using 240-day rolling samples (a time roughly equivalent to one trading year). Fig. 1 shows the time-varying TVS index for the four markets. Most values of the TVS index shown in Fig. 1 are greater than the average TVS index (3.773%) and vary from 2% to 10%. We see several cycles in the dynamic TVS index over the period 2006–2015. The first cycle began in Q1 2006 and ended in Q3 2007, which was the pre-crisis period with a sound set of economic and financial fundamentals (Filardo et al., 2010). During

[7] Note that during the period Q3–Q4 2008, the CSI CFC index declined suddenly from 170 to below 100 due to crisis shocks.

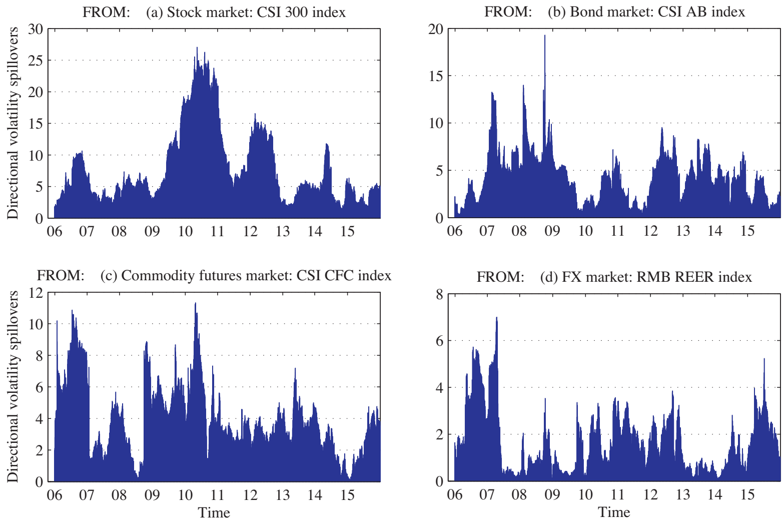

Fig. 2. Dynamic directional volatility spillovers *from* China's (a) stock, (b) bond, (c) commodity futures, and (d) FX markets to other markets. Notes for this and the below figures: The scale ranges of *y*-axis for subfigures are different.

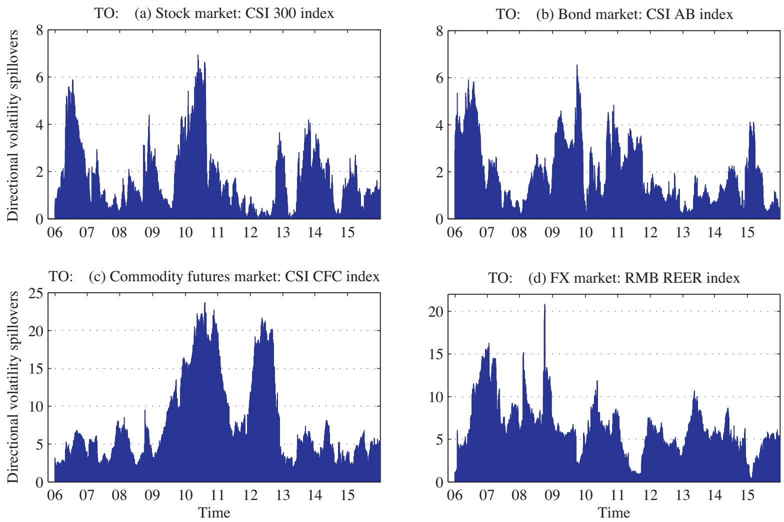

Fig. 3. Dynamic directional volatility spillovers from other markets *to* China's (a) stock, (b) bond, (c) commodity futures, and (d) FX markets.

this period China's stock market experienced a big bull period. For example, the CSI 300 index increased 474%, from 940 at the beginning of 2006 to more than 5400 in Q3 2007. The second cycle started in Q4 2007 and ended in mid-2008, which was the time of US subprime mortgage crisis. During this period, the CSI 300 index in China's stock market dropped from over 5400 to 2400. The third cycle began in Q3 2008 and ended at the beginning of 2009, which was the worst period in the global financial crisis. During this period, the linkages between markets became very tight. The fourth cycle began in 2009 and lasted until the mid-2011, which was the time of the European sovereign debt crisis. To minimize the influence of the global financial crisis on the Chinese economy, the Chinese government announced a 2008–2009 economic stimulus plan, i.e., a RMB 4 trillion stimulus package. This economic stimulus plan had a positive effect on China's financial markets (e.g., from the end of 2008 to the end of 2009 the CSI 300 index rebounded with a 120% increase), but the difficult global economic conditions caused the volatility spillovers in China's financial markets to increase in both intensity and frequency and reach record levels in Q1 2010. The fifth cycle began at the end of 2011 and ended at the beginning of 2013, and during this period stocks experienced a bear market. In the most recent years (2014–2015), the values of the TVS index have been relatively low and have exhibited no obvious pattern.

Figs. 2 and 3 show the dynamic directional volatility spillovers (DVS) *from* and *to* each market, respectively. Fig. 2 shows that on average the largest DVS to other markets is from the stock market followed by the bond, commodity futures, and FX markets in turn. This suggests that the stock and bond markets are the top two volatility spillover transmitters. The DVS

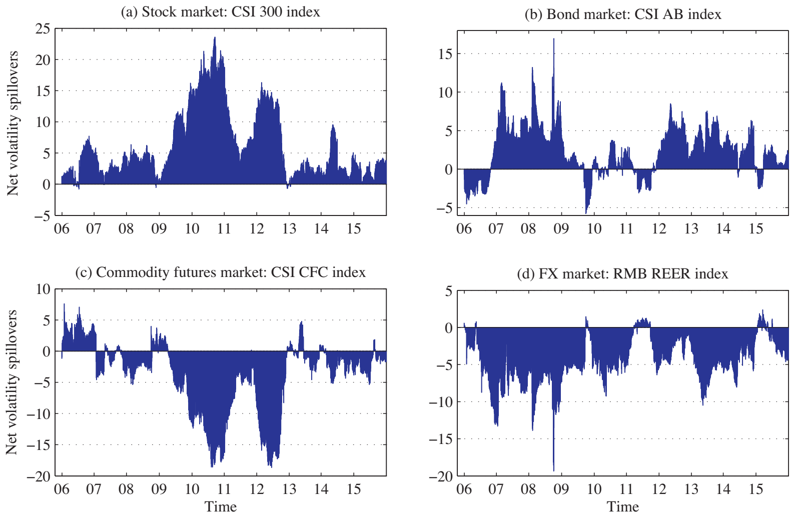

Fig. 4. Dynamic net volatility spillovers for China's (a) stock, (b) bond, (c) commodity futures, and (d) FX markets.

from other markets to each market in Fig. 3 indicates that the commodity futures and FX markets are the top two recipients of volatility spillovers.

To determine which markets are net senders and which are net recipients of volatility spillover, in Fig. 4 we present the dynamic net volatility spillovers from one market to all the other markets. We find that the stock market is the biggest net sender of volatility spillovers. During the global financial crisis and the European sovereign debt crisis (2009–2012) in particular, the net volatility spillovers of the stock market exhibited two huge peaks, with a highest value of 24%. The bond market is the second net sender of volatility spillovers. There are two major periods when net volatility spillovers from the bond market to other markets occurred, (i) from 2007 to mid-2009 during the global financial crisis and (ii) from 2012 to 2014 during the bear stock market. This indicates that there is a "flight-to-quality" from other markets to the bond market during crisis periods that increases the net volatility spillovers from the bond market to other markets. The commodity futures and FX markets are two net recipients of volatility spillovers, but they exhibit different patterns. The net recipient behavior of the commodity futures market mainly occurs during the period 2009–2012 (see the two deep valleys), but during the entire 2006 to 2015 period the FX market is almost always the net recipient of volatility spillovers.

To quantify the contribution of one market to the volatility shocks in another market in net terms, we examine the dynamic net pairwise volatility spillovers (NPVS) between each pair of markets (see Fig. 5). Fig. 5(a) shows that the NPVS between the stock and bond markets changes over time with positive and negative values, indicating a "flight-from-quality" from the bond market to the stock market and a "flight-to-quality" in the opposite direction. Fig. 5(b) shows that almost all the values of NPVS between the stock and commodity futures markets are positive, indicating that the stock market is the net sender of volatility spillovers to the commodity futures market and that the commodity futures market acts as a risk transferring and dispersing platform for the stock market. Fig. 5(c) shows that on average the stock market is the net sender of volatility spillovers to the FX markets, suggesting that although China has a high foreign trade dependence ratio, the influence of stock price fluctuations on the movements of the exchange rate is greater than the impact of the latter on the former and thus the stock market takes the lead. This can be explained using a "stock-oriented" model in which a bullish (bearish) domestic stock market will attract (repel) flows of foreign capital, thereby leading to an increase (decrease) in the demand for a country's currency and an appreciation (depreciation) of the exchange rate. In a manner similar to the dynamic between stock and bond markets, there are "flight-from-quality" and "flight-to-quality" behaviors between the bond and commodity futures markets [see Fig. 5(d)]. Figs. 5(e) and 5(f) show that the FX market is the net recipient of volatility spillovers from the bond and commodity futures markets.

4. Conclusion

We have examined volatility spillovers across China's stock, bond, commodity futures, and FX markets and have described their dynamic behavior using the spillover index method. We have found that these four markets are not well integrated. The stock market is the largest net sender of volatility spillovers to other markets, followed by the bond market. In contrast, the FX and commodity futures markets are the big net recipients of volatility spillovers. For market participants and policymakers our findings provide crucial information about volatility spillovers in China's financial markets.

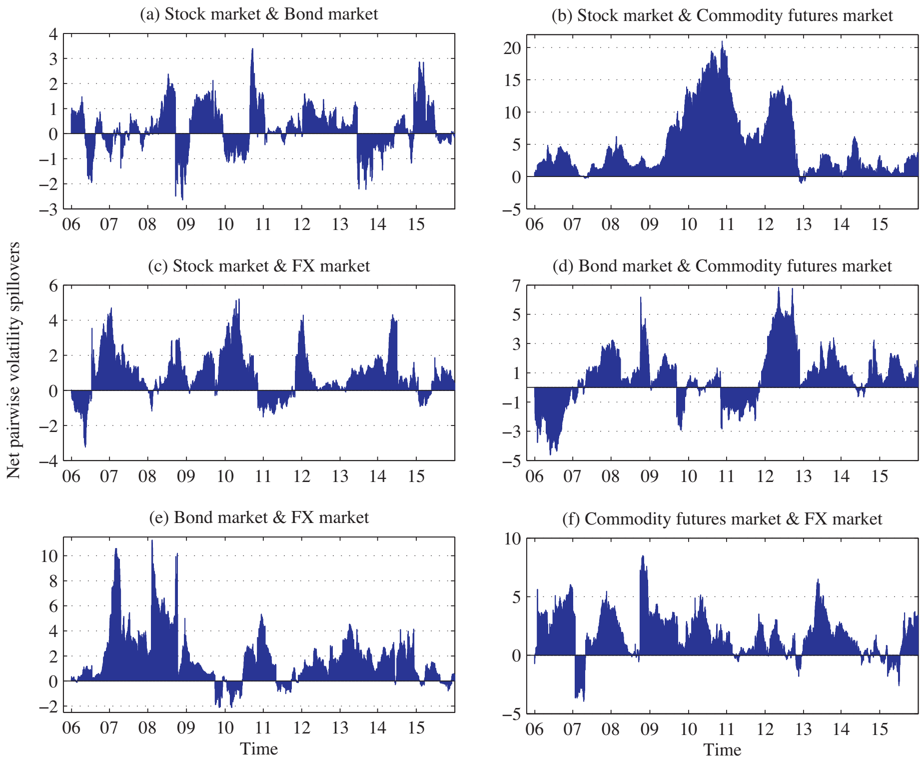

Fig. 5. Dynamic net pairwise volatility spillovers for each pair of China's financial markets.

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References

Aftab, M., Ahmad, R., Ismail, I., 2015. Dynamics between currency and equity in Chinese markets. Chinese Manage. Stud. 9, 333–354.
Antonakakis, N., Kizys, R., 2015. Dynamic spillovers between commodity and currency markets. Int. Rev. Financ. Anal. 41, 303–319.
Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66, 47–78.
Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Econometr. 18, 1–22.
Batten, J.A., Ciner, C., Lucey, B.M., 2015. Which precious metals spill over on which, when and why? some evidence. Appl. Econ. Lett. 22, 466–473.
Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecasting 28, 57–66.
Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. J. Econometrics 182, 119–134.
Filardo, A., George, J., Loretan, M., Ma, G., Munro, A., Shim, I., Wooldridge, P., Yetman, J., Zhu, H., 2010. The international financial crisis: Timeline, impact and policy responses in Asia and the Pacific. BIS Papers 52, 21–82.
Forsberg, L., Ghysels, E., 2007. Why do absolute returns predict volatility so well? J. Financ. Econometrics 5, 31–67.
Hatemi-J, A., 2008. Tests for cointegration with two unknown regime shifts with an application to financial market integration. Emp. Econ. 35, 497–505.
Inclan, C., Tiao, G.C., 1994. Use of cumulative sums of squares for retrospective detection of changes of variance. J. Am. Stat. Assoc. 84, 913–923.
Klößner, S., Wagner, S., 2014. Exploring all VAR orderings for calculating spillovers? yes, we can!—a note on Diebold and Yilmaz (2009). J. Appl. Econometrics 29, 172–179.
Li, X.M., Zou, L.P., 2008. How do policy and information shocks impact co-movements of China's T-bond and stock markets? J. Bank. Finance 32, 347–359.
Lucey, B.M., Larkin, C., O'Connor, F., 2014. Gold markets around the world—who spills over what, to whom, when. Appl. Econ. Letters 21, 887–892.
Weber, E., Zhang, Y., 2012. Common influences, spillover and integration in Chinese stock markets. J. Emp. Finance 19, 382–394.
Yarovaya, L., Brzeszczyński, J., Lau, C.K.M., 2016a. Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. Int. Rev. Financ. Anal. 43, 96–114.
Yarovaya, L., Brzeszczynski, J., Lau, C.K.M., 2016b. Volatility spillovers across stock index futures in Asian markets: Evidence from range volatility estimators. Finance Res. Lett. doi:10.1016/j.frl.2016.03.005.
Yarovaya, L., Lau, M.C.K., 2016. Stock market comovements around the global financial crisis: Evidence from the UK, BRICS and MIST markets. Res. Int. Bus. Finance 37, 605–619.
Zhao, H., 2010. Dynamic relationship between exchange rate and stock price: Evidence from China. Res. Int. Bus. Finance 24, 103–112.