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Financial Spillovers and Spillbacks: New Evidence from China and the G7 Countries

Abstract:

With the increasing openness of the Chinese economy, Chinese financial markets are becoming more integrated with those in developed markets. The goal of this paper is to comprehensively investigate the spillovers and spillbacks in stock, bond, and foreign exchange markets between China and the G7 countries using data from 2000 to 2018. Four important findings emerge: (1) financial spillovers account for a large proportion of the variations in bond, stock, and foreign exchange markets, indicating that the international spillover effect has become an important driver of asset prices; (2) Chinese financial markets have a growing impact on global financial markets over time, especially during periods of turbulence; (3) spillovers from the G7 to China are still higher than the spillbacks from China, suggesting that Chinese markets are more influenced by the financial markets in the G7 conomies than the other way around; (4) economic policy uncertainty is the main driver of cross-border financial spillovers. Our findings have important implications for policy makers who aim to promote international macroprudential policy coordination.

Keywords: Financial spillovers, financial spillbacks, emerging markets, VAR model, transmission channels

JEL classifications: C32, F36, G15

1. Introduction

International financial integration and liberalization has made financial markets across countries increasingly interconnected. Economic and financial linkages between emerging markets and developed markets have also grown substantially in recent years. A better understanding of interaction and financial spillovers among various financial markets is important for investors and policy makers. Agénor and Pereira da Silva (2018) define cross-border financial spillovers as circumstances in which fluctuations in the price of a financial asset in one country (or region) cause variations in the prices of the same asset or other assets in another country (or region). Many studies suggest that financial market fluctuations in advanced economies have large spillover effects on the rest of the world, especially on emerging market economies over the past decade. For instance, Bagliano and Morana (2012) find that the real effects of financial shocks within the US can significantly influence the world economy through the asset prices channel. Syriopoulos et al. (2015) demonstrate that shocks and volatility transmission effects exist between the stock markets in the US and Brazil, Russia, India, and China (BRICs). Georgiadis (2016) shows that the US monetary policy shocks have considerable spillovers to the rest of the world. Similar studies include Forbes and Rigobon (2002), Bianconi et al. (2013), Gauvin et al. (2014), Neely (2015), Engel (2016), Ahmed et al. (2017), Aizenman et al. (2017), Chuliá et al. (2017a, b), Yang and Zhou (2017), and Miranda-Agrippino and Rey (2020).

Some recent studies show that financial market shocks in some emerging economies have been transmitted back, and to a greater extent, to the markets in advanced economies. Gelos and Surti (2016) and Huidrom et al. (2016) show the increasing importance of financial spillovers from emerging economies in the 2000s, especially since the global financial crisis. Similar studies focusing on the spillbacks of the equity market include Dimitriou et al. (2013), Li and Giles (2015), and Shen (2018), among others. Therefore, cross-border financial spillovers have become a two-way street - with the potential to increase financial instability in both directions. Spillbacks, spillovers from emerging markets to advanced economies, may play an important role in driving the global financial turbulence. However, less attention has been paid to the financial spillbacks to advanced economies from the developing and

emerging market economies.

In 2010, China surpassed Japan to become the world's second-largest economy, and the Chinese market has become increasingly important in the global financial market since then. On the one hand, Chinese financial markets affect global markets through direct channels. China's foreign assets and liabilities in 2015 totaled 11 trillion US dollars, which were comparable to those of Japan and France. China's external exposure equals that of Russia, Mexico, Brazil, Indonesia, and Turkey combined. Therefore, Chinese financial markets have become increasingly influential in global financial markets. For instance, the crash of the Chinese stock market in January 2016 significantly affected major asset prices all over the world. On the other hand, Chinese financial markets can influence the financial markets in developed countries through indirect channels. The fluctuations in the Chinese market can affect investors' expectations on the growth of the Chinese economy as well as the world economy, and then affect the financial stability of global financial markets (Mwase et al. 2016). Therefore, understanding the financial spillbacks from China to advanced economies is likely to become more important from the perspective of macroprudential policy.

More recently, several studies have specifically investigated the spillovers from the Chinese market to developed markets. Granville et al. (2011) study production price and exchange rate interdependence between China and G3 (the US, Japan and the Euro-zone), and they find that the impact of Chinese prices on the G3 is more powerful than the impact of the renminbi (RMB) exchange rate. Zhou et al. (2012) find that the US market had dominant volatility impacts on the rest of the world during the 2007-2008 global financial crisis. They also show that volatility in the Chinese stock market has a significantly positive impact on other markets, and the volatility interactions are more evident among the Chinese, Hong Kong, and Taiwanese markets. Their results also indicate that Asian stock markets have become increasingly interdependent in recent years. Mwase et al. (2016) find that recent developments in the Chinese economy and financial markets have a pronounced impact on global financial markets because of the central role that China plays in goods trade and commodity markets, and they also show that this impact is more significant for bad news than for good news. Liow et al. (2018) study the spillovers and interactions in stock, real estate,

bond, and foreign exchange markets across China and six advanced economies. They provide solid evidence that international economic policy uncertainty spillovers drive financial market stress spillovers. Existing studies mainly focus on the degree of volatility spillovers between the Chinese and developed markets; however, less attention has been paid to the transmission channels of spillovers.

The main purpose of this paper is to comprehensively analyze the financial spillovers and spillbacks between China and the G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) in bond, stock, and foreign exchange markets. The paper makes four contributions to the literature. First, we show the significant impact of financial spillovers and spillbacks across countries to variation in asset prices. Second, we quantify the degree and dynamics of spillbacks from China to advanced economies. Our study can enhance understanding of China's impacts on different financial markets. Third, we identify the transmission channels of financial spillovers and spillbacks between China and the G7 economies. Our findings can help international investors better understand the mechanism of risk transmission across countries and may provide additional insights into the asset allocation decision and risk hedging in China and the G7 countries. Finally, some policy implications of our findings are discussed.

2. Model Specifications

We investigate the spillbacks from China to the G7 countries among three major financial markets: stocks, bonds and exchange rates using the measures of the total and directional volatility spillovers proposed by Diebold and Yilmaz (2009, 2012). Their measure is based on a generalized vector autoregressions (VAR) framework in which forecast-error variance decompositions are invariant to the order of variables. In this paper, we use the stock index return and volatility as endogenous variables of VAR model.¹ Specifically, a covariance stationary *N*-variable VAR(*p*) representation is

$$Xt = i = l P \Phi i Xt - i + \varepsilon t, \ \varepsilon \sim i.i.d.0, \Sigma$$
(1)

The moving average can be represented as

¹ More details on the calculations for index return and volatility can be found in Section 3.

$$Xt = i = 0 \infty Ai\varepsilon t - i \tag{2}$$

where coefficient matrices follows the N × N A_i the recursion $Ai = \Phi I Ai - I + \Phi 2 Ai - 2 + \dots + \Phi P Ai - P$, where A0 is an $N \times N$ identity matrix and Ai = 0 for $i < \infty$ θ . The variance decompositions enable us to decompose the forecast error variance of each variable into parts caused by different system shocks. Specifically, we can measure the proportion of the H-step-ahead error variance in forecasting xi, which is caused by the shocks to xi, $\forall j \neq i$, for each *i*.

The traditional VAR model uses Cholesky factorization to achieve orthogonality. However, the forecast error variance decomposition obtained from Cholesky factorization is dependent on the ordering of the variables, which might reduce the robustness of the spillover index based on that. To address this problem, we use the generalized variance decomposition of Koop et al. (1996) and Pesaran and Shin (1998) to decompose variance and identify contemporaneous causal relations between variables. The most important superiority of their generalized method is that the variance decompositions are invariant to the ordering of the variables (Diebold and Yilmaz, 2012).

The *H*-step-ahead forecast error variance decompositions can be denoted by $\theta i j g H$,

$$\theta i jg(H) = \sigma i i - 1h = 0H - 1(ei'Ah\Sigma e_j) 2h = 0H - 1(ei'Ah\Sigma Ah'e_i)$$
(3)

where \sum denotes the variance matrix for the error vector ε ; σjj denotes the standard deviation of the error term for the *j*th equation; and *ei* denotes the selection vector of one as the *i*th element and zeroes otherwise. The discussion of Diebold and Yilmaz (2012) indicate that the sum of the elements in each row of the variance decomposition does not equal 1, namely, $j=1N\theta ijg(H)\neq 1$.

Then, we normalize each entry of the variance decomposition matrix by the row sum to take all available information in matrix into account:

$$\theta i j g(H) = \theta i j g(H) j = l N \theta i j g(H)$$
(4)

where $j=1N\theta i jg(H)=1$ and $i, j=1N\theta i jg(H)=N$. $\theta i jg(H)$ is the H-step-ahead error variances

in forecasting of the *i*th endogenous variable due to the shock from the *j*th endogenous variable. In our study, it represents the spillovers from the financial market of *j*th country to the one of *i*th country. Note that, $i \neq j$ because of the externality nature of spillover.

Several spillover indexes can be constructed using $\theta i jg(H)$. First, we construct the total spillover index of the entire system *TotalspillH*:

$$TotalspillH=i, j=l j \neq l N \theta i jg H i, j=l N \theta i jg H \times 100 = \& i, j=l \& j \neq i N \theta i jg H N \times 100$$
(5)

Eq. (5) shows that *TotalspillH* is the ratio of the sum of the off-diagonal elements in each row of the forecast error variance decompositions table to the sum of all the elements in each row. This index measures the spillover effect of the entire financial system for all the selected countries. We can use rolling windows to calculate *TotalspillH* to capture dynamic spillovers across countries. In general, high or rapid increase in *TotalspillH* normally indicates high spillover risk, as well as high systemic risk.

The second index is *FromspilliH*, which measures the directional spillovers received by market *i* from all other markets *j*. A higher value indicates that the financial market of country *i* is influenced more by the markets of other countries. *FromspilliH* not only can help us monitor the dynamics of spillover risk of one country, but also can tell us which one is more affected by the markets of other countries. Note that the spillover index used in the literature normally refers to *FromspilliH*.

$$From spilliH = \&j = 1 \& j \neq i N \theta i jg H i, j = 1 N \theta i jg H \times 100 = \&j = 1 \& j \neq i N \theta i jg H N \times 100$$
(6)

The third index is TospilliH, which measures the directional spillovers transmitted by market *i* to all other markets *j*. A higher value of TospilliH indicates a larger impact of

country *i* on other countries. This index is particularly useful in systemic risk monitoring because it shows which country's financial market is systemically important. Most of the literature on financial contagion across different countries focuses on financial spillovers from developed countries to emerging markets, however, this study pays more attention to financial spillbacks from the Chinese market to developed countries.

$$To spill i H = \& j = 1 \& j \neq i N \theta j i g H i, j = 1 N \theta j i g H \times 100 = \& j = 1 \& j \neq i N \theta j i g H N \times 100$$

$$(7)$$

In Eqs. (5), (6), and (7), *TotalspillH* satisfies additivity, namely, *TotalspillH* equals the aggregation of *FromspilliH* or *TospilliH* indexes from all the countries in the system. Thus, *FromspilliH* and *TospilliH* are essentially two measures of spillover contributions from different directions. The former measures contributions of spillovers from the perspective of the receiver and the latter measures contributions of spillovers from the perspective of the sender. In general, much more attention should be paid to the country with a large value of either *FromspilliH* or *TospilliH*.

The fourth index is the index of net spillover NetspilliH, measuring the net spillovers from market *i* to all other markets *j*. Note that NetspilliH can be negative, which is different from the first three non-negative indexes. A positive NetspilliH implies that country *i* is a risk sender whereas a negative value implies that country *i* is a risk receiver.

NetspilliH=TospilliH-FromspilliH=&j=1&j≠iN0jigHN-&j=1&j≠iN0ijgHN×100 (8) Thus, *TotalspillH* is essentially a time-dimension measure of systemic risk, and the other three are cross-sectional dimension measures.

Based on these indexes in the literature, we propose the fifth index *Pairspill*, to measure the pairwise spillover effect between the financial markets in two countries from a network perspective. For instance, *Pairspilli* \rightarrow *j* represents the spillovers transmitted from country *i* to country *j*. Unlike Diebold and Yilmaz (DY; 2012), which focus only on the net pairwise spillovers, *Pairspill* measures pairwise spillovers. This measurement has some advantages over DY's net spillover measure: First, because *FromspilliH*, *TospilliH* and *NetspilliH* are directly constructed by pairwise spillovers, we can further investigate these indexes at a more micro-level by analyzing *Pairspill*. Second, pairwise spillovers are the microfoundation of systemic risk. Moreover, *Pairspill* is asymmetric, which means the *Pairspilli* \rightarrow *j* and *Pairspillj* \rightarrow *i* are not equivalent.

$$Pairspilli \rightarrow jH = \theta jigH \times 100 \quad i \neq j \tag{9}$$

3. The Data

This study investigates spillovers and spillbacks in the financial markets between China and the G7 countries. Unlike most of the previous studies, which focus on one market, we take a broader view by considering the bond, stock, and foreign exchange markets. Our bond market data cover the period July 3, 2007 to December 31, 2018, and the market proxies are 10-year government bonds in each country. The daily observations total 3,000. The stock returns data for each country are represented by stock indexes in US dollars: CSI 300 (China), S&P/TSX (Canada), CAC 40 (France), DAX 30 (Germany), FTSE MIB (Italy), Nikkei 225 (Japan), FTSE 100 (UK), and S&P 500 (US). Our stock data were gathered over the sample period beginning from April 12, 2005 to December 31, 2018, with a total of 3,580 observations. All exchange rates except USD are expressed as foreign currencies per US dollar: CNY/USD, CAD/USD, EUR/USD, JPY/USD, and GBP/USD. The US exchange rate is expressed in US dollars, which is the world's most widely recognized, publicly traded currency. The data span the period January 18, 2000 to December 31, 2018, with a total of 4,945 observations. All data come from Datastream.

In order to control for nonsynchronization problems caused by the fact that markets in different countries are not open during the same hours, we calculate stock returns as two-day rolling-average returns based the stock market index in each country. Suppose the stock index

price is P_t and Pt is the two-day rolling-average price

$$Pt = Pt + Pt - 1/2 \tag{10}$$

Then the logarithmic return is

$$rt = lnPt - lnPt - l \times 100 \tag{11}$$

For the returns on US exchange rate, we take the negative value of the original log return obtained from Eq. (11). Given the value of log returns, we use the AR-GARCH model to obtain the daily volatility for each market. Tables 1, 2, and 3 report the summary statistics of two-day average prices, log returns and volatility of bond, stock, and foreign exchange markets, respectively. In general, we find that stock markets have relatively higher returns and volatility than the other two markets, which is in line with the findings in the literature.

[Insert Tables 1, 2, 3 about here]

We construct VAR models for log returns and volatility in the three markets. More specifically, we use VAR(8) for the bond, stock, and foreign exchange markets to construct the VAR(6) model. The maximum lag is 12 periods, and the optimal lag order of the following models are selected by the Schwarz information criterion (SIC): the VAR(8) model of order 6 for bond market return; the VAR(8) model of order 1 for bond market volatility; c. VAR(8) model of order 7 for stock market return; the VAR(8) model of order 5 for stock market volatility; the VAR(6) model of order 10 for foreign exchange market returns; and the VAR(6) model of order 6 for foreign exchange market volatility.

We construct the spillover index based on generalized variance decompositions of 20-day-ahead return/volatility forecast errors estimated by a 120-day rolling window (half year). To better display the results, we average the daily spillover index to obtain weekly index. In addition, for pairwise spillovers, we report only the monthly average results because of space limitations.

To further identify transmission channels associated with financial spillovers and spillbacks, we perform a regression analysis using six categories of data: cross-border capital flow (quarterly), import and export trade (quarterly), leverage (monthly), economic policy uncertainty (monthly), country risk (monthly), and financial conditions (monthly). The variables are selected using three criteria. The first criterion is data availability, and the second one is data frequency. Because the spillover and spillback indexes in our regression analysis are on a quarterly or monthly basis, all data must be available at the same frequency (quarterly or monthly). Third, we select macrofinancial data, instead of macroeconomic data because the former are somewhat more sensitive to spillover risk than the latter.

Specifically, the cross-border capital flow data include some indicators for the capital and financial accounts in the balance of payments: direct investment, equity portfolio investment, bond portfolio investment, and other investments. These indicators represent the capital inflow and outflow in China, and a higher value indicates a larger capital flow. The import and export trade data include two Purchasing Managers Indexes (PMI): the new export orders and imports. A higher PMI indicates more active cross-border trade. The leverage data include leverage ratios for the household, non-financial counterparty (NFC), government and financial sectors. These data are collected from the WIND database. To measure the policy risk of the Chinese market, we use the China Economic Policy Uncertainty (EPU) index of Huang and Luk (2020). Furthermore, to investigate different channels associated with spillovers and spillbacks, we use four policy-specific uncertainty indexes-fiscal policy uncertainty (FPU), monetary policy uncertainty (MPU), trade policy uncertainty (TPU), and exchange rate and capital account policy uncertainty (EXCAPU).² The country risk data are collected from the EIU Country Risk Service. Specifically, country risk is measured in terms of currency risk, sovereign debt risk, banking risk, political risk and economic structure risk.³ To access the financial conditions of the Chinese market, we collect the China Financial Condition Index (CFCI) from the Yicai Research Institute. This index uses a z-score to capture the most important information and changes in China's interbank lending market, bond market, stock market and bank credit and other financing channels. A z-score above zero represents a relatively tight financial environment, and a score below zero represents a relatively loose financial environment. The higher the CFCI, the tighter the Chinese financial environment and the greater the stress on the financial market.

² All the policy uncertainty data are available at: <u>https://economicpolicyuncertaintyinchina.weebly.com/</u>.

³ More details about country risk data can be found at:

https://store.eiu.com/SampleFileHandler.ashx?pubtypeid=60000206&mode=_toc.pdf.

4. Empirical Analysis

4.1. Total Spillover Analysis

Our sample period covers the 2008 global financial crisis, the 2009 European debt crisis as well as the recent China-US trade friction. The dynamics of financial spillovers/spillbacks across counties in different periods is often found to be insufficiently captured by static analysis. Therefore, we estimate dynamic spillover (spillback) indexes using a rolling window instead of a static one.

[Insert Figure 1 about here]

Figure 1 plots the total spillovers, which measure the contribution of spillovers of shocks across all countries to the total forecast error variance, for bond, stock and foreign exchange markets. The three graphs on the left show the total return spillover indexes and those on the right plot the total volatility spillover indexes for all markets, respectively. We find that financial spillovers account for a large proportion of the variation in bond, stock, and foreign exchange markets, which indicates that international spillovers are an important driver of asset price movements. Our findings are in line with the results of Gelos and Surti (2016), who find that about 70%-80% of equity and foreign exchange returns in both developed and emerging economies are attributable to international factors. Also, the first row of each panel in Table 4 reports the estimations of return and volatility spillovers and spillbacks for bond, stock, and foreign exchange markets. On average, 66.7% of the variation in bond returns and 51.09% of the variation in bond volatility come from spillovers in the bond market. In the stock market, 74% of the variation in market returns and 68.86% of the variation in market volatility come from the spillover effect. Moreover, 61.16% of the variation in currency returns and 46.07% of the variation in currency volatility come from the spillover effect. Thus, the spillover effect makes the largest contribution to fluctuation in the stock market, followed by the bond market, and finally, the foreign exchange market. This suggests that, among the three markets, the stock market is the most influenced by spillovers from other countries whereas the foreign exchange market is least influenced. This is probably caused by the fact that the G7 countries in the eurozone (France, Germany, and Italy) use the same currency, and

thus when we estimate the total spillover index, only six currencies are considered (more details can be found in Section 3).

[Insert Table 4 about here]

Measuring both return and volatility spillovers is not only useful but also necessary, because these two indexes assess spillover risk from two different perspectives. The return spillover index measures risk of the first moment of asset returns and the volatility spillover index represents the second moment. Table 2 also indicates that on average the total return spillover indexes are on average higher than the total volatility spillover indexes in all three markets.

4.2. Spillback Analysis

The third row in each panel of Table 4 shows the statistics for different spillback indexes. First, the return spillbacks from China to the G7 in the foreign exchange market are strongest among all the markets and account for 38.89% of the variation in G7 stock market returns. Second, the Chinese stock market has the second strongest return spillbacks and about 30.96% of the variation in G7 stock market returns can be traced to spillbacks from China. Third, 27.09% of the variation in G7 bond market returns can be explained by spillovers from China's bond market. In terms of volatility spillbacks, the Chinese stock market has the strongest spillbacks explaining 34.43% of the G7 stock market volatility, followed by the foreign exchange market (27.74%) and the bond market (19.60%).

In general, we find that the impact on the G7 countries is more significant from China's foreign exchange market and stock market than from the bond market. This is probably because that the foreign exchange market and the stock market have a higher degree of financial integration. Specifically, China's foreign exchange market and bond market tend to affect the G7 countries via return spillovers, while China's stock market tends to influence the G7 countries via volatility spillovers.

In addition to investigating the average behavior of spillbacks, we further explore its evolution during our sample period. Figure 2 presents the spillbacks that China generates for the G7 using a 120-day rolling window. The three graphs on the left show the total return spillback indexes and those on the right plot the total volatility spillbacks for the bond, stock,

and foreign exchange markets, respectively. The graph for bond market volatility spillovers shows that China has had an increasing and significant impact on bond markets in the G7 economies. The volatility spillbacks in the stock market rise significantly in 2007, 2015, and 2018, and the foreign exchange market volatility spillovers have substantial increases in 2005 and 2015. Overall, we find that the volatility spillbacks in all markets are significantly stronger and more volatile around 2015. This greater intensity of spillbacks is likely caused by the large financial market turbulence in China in 2015, especially the bursting of the stock market bubble.

[Insert Figure 2 about here]

4.3. Spillovers Analysis

The second row in each panel of Table 4 shows the statistics for different spillover indexes. China's stock market suffers the most spillover effects, and 56.01% (49.20%) of the variation in its return (volatility) can be explained by the G7 stock market spillovers. Next, 54.16% (32.18%) of the variation in return (volatility) in China's foreign exchange market can be explained by the G7 foreign exchange market spillovers, and the 41.56% (28.69%) of the variation in return (volatility) in China's bond market can be explained by the G7 bond markets spillovers.

Overall, we find that the Chinese stock market is mostly affected by international markets, followed by the foreign exchange market and the bond market in that order, because of greater development of the stock and foreign exchange markets. Figure 3 plots the spillover indexes, measuring the contribution of spillovers of shocks from the G7 countries to the total forecast error variance in the Chinese bond, stock, and foreign exchange markets. The three graphs on the left show the total return spillovers and those on the right plot the total volatility spillovers for all markets, respectively.

[Insert Figure 3 about here]

We have several overall findings from the analysis of spillovers. First, Chinese financial markets are increasingly affected by global financial markets over time, especially during periods of turbulence—for example, the 2008 global financial crisis, the 2009 European debt crisis, and the China-US trade friction that started in 2017. Second, Chinese financial markets

were highly volatile in 2015, and spillovers from the G7 countries to China substantially increased, indicating that the high volatility in Chinese financial markets can be attributed in part to the propagation of shocks from global financial markets.

4.4. Net Spillover Analysis

The fourth row in each panel of Table 4 shows the statistics for net spillback effects, which is the difference between spillback and spillover effects. If the net spillback is positive, it means that the spillback effect is larger than the spillover effect. We find that, all three markets have negative net spillback effects, indicating that the spillover effects from the G7 are greater than the spillback effects from China, indicating that the G7 are the main component of the global financial market.

The dynamic changes of net spillbacks from China to the G7 economies in the three markets are presented in Figure 4. We conclude as follows. First, the net spillback effect is negative throughout the sample period, indicating that financial market in the G7 play a greater role in spillovers than those in China, and this conclusion is stronger during the period of the 2008 global financial crisis and the 2009 European debt crisis. Second, China's net spillbacks increase and even become positive in 2015 and 2017-2018, which indicates that China's financial market has become more important than before. Third, the net spillback effect is greater via the volatility channel than via the return channel.

[Insert Figure 4 about here]

4.5. Pairwise Spillover Analysis

Figure 5 presents the dynamic trends of pairwise spillover effects between China and the G7 countries in the bond market. Figures 5a-g are based on market return and the rest are based on market volatility. Table 5 shows the descriptive statistics of pairwise spillovers.

[Insert Table 5 about here]

Overall, in the US and Canada, the spillover effects are consistently larger than the spillback effects in the bond markets, indicating that they have larger effects on China's bond market. In addition, in the UK, returns and volatility on the bond market also have larger effects on China's bond market. Second, both pairwise volatility spillovers and spillbacks tend to become large over recent years, because Chinese financial markets have become

increasingly interdependent with the G7 markets. This result is generally consistent with the findings in Section 4.2 and 4.3.

The dynamic trends of pairwise spillover effects between China and the G7 countries in the stock market are presented in Figure 6. Figures 6a-g show the return spillovers and the rest of figures present the volatility spillovers. Overall, we find that the stock market spillovers from the G7 are significantly greater than the spillbacks from the Chinese market throughout the period. This suggests that China has a smaller impact on the G7 stock markets than the G7 markets have on the Chinese stock market. Also, we find that the differences between pairwise volatility spillovers and spillbacks in the stock market seem to be insignificant.

Figure 7 presents the dynamic changes in pairwise spillovers between China and the G7 countries in the foreign exchange market. Figures 7a-e show that, the return spillovers from the US dollar, the pound, and the euro seem to be much stronger than the spillbacks from the RMB, suggesting that the currencies of developed economies have larger impact on the RMB than the other way around. Figures 7f-l show that the differences between volatility spillovers and spillbacks seem to be insignificant for all currencies.

[Insert Figures 5, 6, 7 about here]

4.6. Generalized Impulse Response Analysis

In this section, we use the generalized impulse response analysis of Koop et al. (1996) and Pesaran and Shin (1998) to analyze the response of financial markets in one country to the shocks from another country by an increase of one standard deviation. This not only helps us to understand changes in the financial market from the perspective of cross-country spillovers, but also helps the government to take effective steps to eliminate international shocks and international investors to adjust their portfolio timely.

The impulse response results between China and the G7 countries in the bond market are illustrated in Figure 8. We find that positive spillovers exist across countries. Specifically, if one country's bond return increases by one standard deviation, other countries will also experience an increase in the bond market. This indicates that the global financial markets are well integrated, and international spillovers are an important driver of changes in the bond

market in each country. In addition, Figure 8 indicates that shocks from the G7 has longer impacts than those from China. Specifically, the bond return in the G7 will increase during the first 2 periods response to the shock from China. In contrast, China's bond return will increase during the first 6 periods response to the shock from the G7. Impulse responses among the volatilities in the bond markets have similar results.

[Insert Figure 8 about here]

Figure 9 presents the impulse response results between China and the G7 countries in the stock market. As in the bond market, positive spillovers also exist between different stock markets. Moreover, we find that shocks from the G7 have shorter impacts than those from China. Specifically, stock returns in the G7 increase during the first ten periods in response to a shock from China. In contrast, China's stock returns increase during the first two periods in response to a shock from the G7. Similar results also apply to the impulse responses for volatility in the stock markets.

[Insert Figure 9 about here]

The impulse response results between China and the G7 countries in the foreign exchange market are shown in Figure 10, which leads to three interesting findings. First, positive spillover effects exist between countries. This finding is consistent with that for the bond and stock markets. Second, shocks from the G7 have impacts similar to those from China in terms of duration. Specifically, the stock returns in the G7 increase during the first two to three periods in response to a shock from China. In contrast, Chinese stock returns increase during the first three periods in response to a shock from the G7. Third, impulse responses for volatility in the stock market have similar results, except that Chinese stock returns have a long-term response and increase during the first ten periods following a shock from the US and Canada.

[Insert Figure 10 about here]

5. Transmission Channels of Financial Spillovers and Spillbacks

Understanding the transmission channels of financial spillovers and spillbacks between China and the G7 is of particular importance for policy makers. It can help them to design effective macroprudential policies to contain cross-border propagation of financial risks and maintain financial stability within and across countries. Thus, we perform a regression analysis to identify six underlying transmission mechanisms of spillovers and spillbacks (cross-border capital flows, import and export trade, leverage, economic policy uncertainty, country risk, and financial conditions). Because the frequency and observations for different data categories are not consistent, we conduct ordinary least squares (OLS) regressions separately for each of them to explicitly examine transmission channels. To control for time trends, we include time variables on a monthly or quarterly basis in the regressions. Table 5 reports the descriptive statistics for selected variables of a variety of spillover channels.

[Insert Table 6 about here]

First, we examine the cross-border capital flow channels of spillovers and spillbacks by regressing *Fromspill* and *Tospill* on inflows and outflows of direct investment, stock portfolio investment, bond portfolio investment, and other investments. Three findings emerge from Table 7. First, cross-border capital flows have the greatest impact on foreign exchange market spillovers, followed by bond market spillovers and finally stock market spillovers. Second, the impacts of different kinds of investment on spillovers differ across markets. Bond market spillovers are mainly affected by the portfolio investment in bonds and other investments. Direct investment is a significant contributor to foreign exchange market spillovers, while portfolio investment is the main source of stock market spillovers. Third, spillovers are affected by capital outflows more than inflows, indicating that risks from the G7 countries are more likely to be transmitted to the Chinese market through China's foreign asset allocation.

[Insert Table 7 about here]

Second, we test the import and export trade channels of spillovers and spillbacks by regressing *Fromspill* and *Tospill* on the PMI of import and export trade. Table 8 shows that all three markets, especially the stock market, are significantly affected by import and export trade. Spillovers and spillbacks are affected by exports more than imports. In other words, exports play a more important role in spillover transmission among economies.

[Insert Table 8 about here]

Third, Table 9 reports the results of regressions that examine the relationship between leverage and spillover transmission. In general, we find that bond market spillovers are

significantly affected by leverage, whereas stock and foreign exchange markets tend to respond less to leverage. At the sectoral level, financial sector leverage has the most significant impact on risk spillovers, whereas government leverage has the least impact. The negatively significant coefficients of the financial sector on the bond and stock markets indicates that a high degree of financial sector leverage may increase the vulnerability of the Chinese financial system and decrease its impact on the G7 economies.

[Insert Table 9 about here]

Fourth, Table 10 presents the regression results of the relationship between EPU and spillover transmission. Bond markets are most affected by EPU, followed by stock and foreign exchange markets. Among all the types of policy uncertainty, trade policy uncertainty is the most significant contributor to spillover transmission, indicating that, because China is the world's largest exporter, changes in its trade policy significantly affects its cross-border spillovers. Specifically, greater trade policy uncertainty is associated with larger spillovers from the G7 to the Chinese bond and stock markets.

[Insert Table 10 about here]

Fifth, we examine the country risk channels of spillovers and spillbacks by regressing *Fromspill* and *Tospill* on currency risk, sovereign debt risk, banking risk, political risk, and economic structure risk. Our results in Table 11 document the importance of country risk channels for all three markets. Specifically, banking risk is the most significant contributor to cross-country spillovers and spillbacks because banking plays the most important role in the Chinese financial system. Moreover, currency risk is also important for spillover transmission and the increase in currency risk tends to weaken China's impact on advanced economies.

[Insert Table 11 about here]

Finally, the regression results of the relationship between financial conditions and spillover transmission are reported in Table 12. We find that the spillovers of bond and foreign exchange markets are highly related to the financial conditions in China. Specifically, deterioration of Chinese financial markets tends to amplify foreign exchange market spillovers and reduce bond market spillovers between China and the G7 countries.

[Insert Table 12 about here]

6. Concluding Remarks

Over the last two decades, the degree of global interconnectedness has significantly increased. Financial markets across countries are becoming increasingly interconnected and interdependent. The contribution of Chinese markets to global economic growth and financial development has increased remarkably over the past decade. This paper analyzes the interactive relationship between China and the G7 countries, to determine whether significant spillbacks (spillovers from emerging markets to advanced economies) are taking place from China to the G7 countries. The empirical findings are as follows.

First, we find that spillovers account for a large proportion of the variation in bond, stock, and foreign exchange markets in general. In particular, total spillovers contribute more than 68% of the stock market variation, more than 51% of the bond market variation, and more than 51% of the foreign exchange market. This indicates that the global financial markets are closely interconnected, and the international spillover effect has become an important driver of asset prices.

Second, we show that Chinese financial markets have an increasing impact on global financial markets over time, especially during the periods of turbulence. More specifically, the Chinese stock market has continuously significant spillback effect on the G7 stock markets. In the bond and foreign exchange markets, the spillbacks from China to advanced economies have increased in magnitude in recent years, indicating the growing importance of Chinese bond and foreign exchange markets in the global financial market. In addition, we find that Chinese financial markets are also increasingly affected by the global financial market over time.

Third, we find that the spillovers from the G7 to China have been consistently higher than the spillback effects from China. Specifically, the net spillovers are negative through the full period, indicating that Chinese markets are influenced by the financial markets of the G7 economies more than the other way around. Return (volatility) spillovers are on average 18 (9) percent higher than return (volatility) spillbacks and these effects are more pronounced during the period of the 2008 global financial crisis as well as the 2009 European debt crisis. Moreover, China's net spillbacks increase and even become positive during 2015 and 2017-2018, indicating the growing importance of Chinese markets for developed markets. The results of our pairwise analysis also confirm these findings.

Fourthly, we use a generalized impulse response function to analyze the response of financial markets in one country to the shocks from another country, and our results demonstrate that the impulse response duration differs substantially between China and the G7 countries. More specifically, in the bond market, shocks from the G7 markets have longer-lasting impacts than those from China. Conversely, in the stock market, responses to shocks from the G7 are of shorter duration than those from China. In the foreign exchange market, shocks from both the G7 and China have relatively short-lived impacts on each other. Our results demonstrate that reactions to shocks from other countries vary across markets.

Finally, we identify spillover channels between China and the G7 economies by conducting a comprehensive regression analysis. Overall, we find that the cross-border financial spillovers are driven by cross-border capital flows, import and export trade, leverage, economic policy uncertainty, country risk and financial conditions. Among all the channels, economic policy uncertainty seems to have the strongest impact on spillover transmission. By contrast, market spillovers across countries tend to be less responsive to changes in the leverage ratio of various sectors in China. Specifically, we show that direct investment, other investments, export trade, leverage in the financial sector, trade policy uncertainty, fiscal policy uncertainty, banking risk, and currency risk are more important drivers than other factors.

Overall, our paper has important implications for policy makers. First, the policy makers in developed countries should increasingly take economic and policy developments in China into account when evaluating macrofinancial conditions for two reasons: The spillbacks from Chinese financial markets, especially the stock and foreign exchange markets, are considerable, and the spillbacks from China to developed markets are significantly stronger during the periods of turbulence. Second, financial regulators in different countries may need to strengthen international macroprudential policy coordination to mitigate the effects of cross-border financial spillovers and spillbacks. Effective macroprudential policies should be implemented to contain the cross-border propagation of financial risk and maintain financial stability within and across countries.

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	Obs.	Mean	SD	Min	Max
Log return (China)	3,000	0.0039	0.303	-1.719	3.140
Log return (US)	3,000	0.0078	0.338	-1.670	1.824
Log return (UK)	3,000	0.0147	0.303	-1.204	2.354
Log return (Japan)	3,000	0.0088	0.127	-0.867	0.758
Log return (Germany)	3,000	0.0158	0.270	-1.656	1.717
Log return (France)	3,000	0.0153	0.262	-1.524	1.694
Log return (Italy)	3,000	0.0106	0.405	-2.781	3.484
Log return (Canada)	3,000	0.0091	0.262	-1.103	1.168
Volatility (China)	3,000	0.2930	0.129	0.127	2.039
Volatility (US)	3,000	0.3310	0.086	0.235	1.225
Volatility (UK)	3,000	0.2940	0.064	0.244	1.195
Volatility (Japan)	3,000	0.1240	0.051	0.064	0.679
Volatility (Germany)	3,000	0.2630	0.072	0.196	1.117
Volatility (France)	3,000	0.2540	0.072	0.178	1.108
Volatility (Italy)	3,000	0.3710	0.188	0.194	2.970
Volatility (Canada)	3,000	0.2590	0.051	0.198	0.697

Table 1: Summary statistics for log returns and volatility in bond markets

Note: This table presents summary statistics for daily log returns (in percentage) and volatility in bond markets during the period from July 3, 2007 to December 31, 2018. Volatility of returns is modeled with a GARCH (1, 1) process.

	Obs.	Mean	SD	Min	Max
Log return (China)	3,580	0.031	1.214	-8.297	7.558
Log return (US)	3,580	0.021	0.786	-6.619	6.204
Log return (UK)	3,580	0.008	0.781	-6.494	5.490
Log return (Japan)	3,580	0.015	1.023	-8.663	8.518
Log return (Germany)	3,580	0.025	0.933	-5.901	6.595
Log return (France)	3,580	0.004	0.942	-6.597	6.521
Log return (Italy)	3,580	-0.016	1.078	-8.880	7.104
Log return (Canada)	3,580	0.011	0.743	-6.627	5.308
Volatility (China)	3,580	1.143	0.479	0.593	6.560
Volatility (US)	3,580	0.723	0.395	0.286	5.204
Volatility (UK)	3,580	0.730	0.335	0.350	4.990
Volatility (Japan)	3,580	0.940	0.390	0.560	6.485
Volatility (Germany)	3,580	0.875	0.367	0.496	4.692
Volatility (France)	3,580	0.890	0.383	0.468	5.169
Volatility (Italy)	3,580	1.019	0.417	0.562	6.153
Volatility (Canada)	3,580	0.680	0.371	0.282	5.190

Table 2: Summary statistics for log returns and volatility in stock markets

Note: This table presents summary statistics for daily log returns (in percentage) and volatility in stock markets during the period from April 12, 2005 to December 31, 2018. Volatility of returns is modeled with a GARCH (1, 1) process.

	Obs.	Mean	SD	Min	Max	
Log return (China)	4,945	-0.0038	0.088	-1.014	1.405	
Log return (US)	4,945	-0.0021	0.217	-1.376	1.364	
Log return (UK)	4,945	0.0050	0.414	-2.613	5.841	
Log return (Japan)	4,945	0.0009	0.440	-2.978	2.341	
Log return (EU)	4,945	-0.0025	0.432	-2.814	2.017	
Log return (Canada)	4,945	-0.0012	0.405	-2.897	2.914	
Volatility (China)	4,945	0.0806	0.056	0.010	1.107	
Volatility (US)	4,945	0.2090	0.062	0.146	0.926	
Volatility (UK)	4,945	0.3981	0.137	0.281	4.006	
Volatility (Japan)	4,945	0.4292	0.099	0.337	1.541	
Volatility (EU)	4,945	0.4220	0.104	0.323	1.762	
Volatility (Canada)	4,945	0.3873	0.129	0.265	2.122	

Table 3: Summary statistics for log returns and volatility in foreign exchange markets

Note: This table presents summary statistics for daily log returns (in percentage) and volatility in foreign exchange markets during the period from January 18, 2000 to December 31, 2018. Volatility of returns is modeled with a GARCH (1, 1) process.

	Re	turn	Volatility			
	Mean	SD	Mean	SD		
		Panel A: Bo	nd Market			
Total spillovers	66.70	3.053	51.09	7.842		
Spillovers from CN	41.56	8.196	28.69	19.04		
Spillbacks from CN	27.09	10.50	19.60	18.33		
Net spillovers from CN	-14.56	12.55	-9.086	10.95		
		Panel B: Sto	ck Market			
Total spillovers	74.01	3.490	68.86	4.595		
Spillovers from CN	56.01	11.23	49.20	14.19		
Spillbacks from CN	30.96	11.53	34.43	21.62		
Net spillovers from CN	-25.06	16.73	-14.77	22.04		
		Panel C: Exchang	ge Rate Market			
Total spillovers	61.16	4.052	46.07	7.432		
Spillovers from CN	54.16	12.19	32.18	12.11		
Spillbacks from CN	38.89	12.53	27.74	14.74		
Net spillovers from CN	-15.27	18.61	-4.443	14.10		

Table 4: Summary statistics for spillover and spillback effects

Note: This table presents summary statistics for daily spillover and spillback indexes including *Totalspill*, *Fromspill*, *Tospill* and *Netspill*.

	Bond Markets					Stock N	Aarkets		Exchange Rate Markets				
	Reti	urn	Volat	ility	Reti	urn	Volat	ility	Reti	urn	Volat	ility	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Spillovers (US→CN)	3.408	1.737	2.841	3.376	4.457	1.908	5.628	3.961	7.108	3.080	4.888	3.902	
Spillovers (UK→CN)	3.585	2.029	2.148	2.506	4.302	2.050	4.727	4.138	7.838	3.131	5.535	3.923	
Spillovers (JP→CN)	4.817	2.546	4.556	6.557	4.985	2.330	6.039	3.646	8.522	4.900	6.135	4.598	
Spillovers (EU→CN)									6.896	3.111	5.339	3.680	
Spillovers (GE→CN)	3.402	2.072	2.072	2.160	4.069	1.913	4.080	3.251					
Spillovers (FR→CN)	3.619	2.003	2.449	2.527	3.962	1.913	3.947	3.448					
Spillovers (IT→CN)	4.446	2.336	3.953	4.269	3.965	1.933	4.193	3.242					
Spillbacks (CA→CN)	3.728	1.835	1.586	1.442	5.215	2.701	5.818	3.753	8.523	3.698	5.840	3.972	
Spillbacks (CN→US)	6.724	2.800	4.819	4.858	8.295	3.114	7.677	4.178	12.47	4.708	7.030	4.059	
Spillbacks (CN→UK)	5.928	2.214	3.055	3.794	7.722	3.134	8.141	3.931	11.14	4.477	5.660	3.757	
Spillbacks (CN→JP)	5.243	2.429	4.502	5.958	7.640	3.136	6.672	3.279	9.538	4.165	6.296	4.450	
Spillbacks (CN→EU)									11.18	4.427	6.958	4.313	
Spillbacks (CN→GE)	5.711	2.204	3.510	3.333	8.034	2.535	6.492	2.963					
Spillbacks (CN→FR)	5.523	2.183	4.611	4.421	7.606	2.586	6.420	3.107					
Spillbacks (CN→IT)	5.761	2.354	5.038	5.221	7.659	2.794	6.023	3.340					
Spillbacks (CN→CA)	6.671	2.636	3.154	3.531	9.058	3.180	7.779	4.097	9.833	3.736	6.235	3.736	
Observations	57	3	57	4	688		682		954		848		

Table 5: Pairwise spillovers and spillbacks for bond, stock and foreign exchange markets

	Variable	Mean	SD	Min	Max
	Quarter	-	-	2000Q2	2018Q4
	Direct investment outflow	0.16	0.17	0.01	0.67
	(×\$100 billion)	0.16	0.17	-0.01	0.67
	Direct investment inflow	0.41	0.24	0.07	1.05
	$(\times$ \$100 billion)	0.41	0.24	0.07	1.05
	Equity portfolio investment outflow	0.04	0.06	0.04	0.10
	(×\$100 billion)	0.04	0.00	-0.04	0.19
	Equity portfolio investment inflow	0.06	0.06	0.07	0.22
	(×\$100 billion)	0.00	0.00	-0.07	0.23
Quarterly data	Bond portfolio investment outflow	0.04	0.11	-0.30	0.42
	(×\$100 billion)	0.04	0.11	-0.50	0.42
	Bond portfolio investment inflow	0.05	0.11	-0.23	0.46
	$(\times$ \$100 billion)	0.05	0.11	0.23	0.10
	Other investment outflow	0.27	0.37	-0.43	1 38
	(×\$100 billion)	0.27	0.57	0.15	1.50
	Other investment inflow	0.11	0.41	-1.18	0.93
	Household Sector (%)	26.53	11.78	12.40	52.10
	NFC Sector (%)	119.88	22.81	92.00	160.40
	Government Sector (%)	30.37	5.08	18.70	38.80
	Financial Sector (%)	40.70	17.22	19.80	72.65
	month	-	-	2000M7	2018M12
	CFCI	0.10	0.97	-1.79	1.94
	PMI export	51.07	4.61	29.00	63.90
	PMI import	49.84	3.37	32.20	57.50
	FPU (×100)	1.12	0.67	0.21	4.51
	MPU (×100)	1.12	0.66	0.18	3.58
Monthly data	TPU (×100)	1.20	1.01	0.25	9.32
	EXACPU (×100)	1.14	0.72	0.20	4.12
	Currency risk	37.15	1.89	33.00	43.00
	Sovereign risk	35.86	3.23	31.00	42.00
	Banking risk	52.89	2.48	45.00	57.00
	Political risk	54.84	1.48	52.00	57.00
	Economic structure risk	33.09	4.00	25.00	38.00

Table 6: Summary statistics for selected variables of spillover channels

Note: This table reports summary statistics for selected variables in a variety of spillover channels. The upper panel reports the variables on a quarterly basis and the lower panel reports the variables on a monthly basis. To control for time trends, we include time variables on a monthly or quarterly basis in regressions. The sample periods for each data category are as follows: cross-border capital flow (2000Q2-2018Q4), leverage (2000Q2-2018Q4), financial conditions (2008M9-2018M12), import and export trade data (2005M1-2018M12), economic policy uncertainty (2000M1-2018M12), country risk (2003M7-2018M12).

		Bond M	Markets			Stock N	Aarkets		Exchange Rate Markets			
	Re	turn	Vola	atility	Re	turn	Vola	atility	Re	turn	Vola	atility
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill
Direct investment outflow	-16.73	-21.02**	-2.15	-13.89	0.44	1.59	-16.41	6.54	9.87	-18.98	-29.56**	-40.52***
	(-1.35)	(-2.06)	(-0.07)	(-0.51)	(0.05)	(0.12)	(-0.57)	(0.21)	(0.52)	(-1.15)	(-2.11)	(-3.13)
Direct investment inflow	5.30	-2.49	3.92	-7.40	2.24	6.15	-11.74	-2.89	-6.48	-18.09**	-4.89	-5.72
	(0.70)	(-0.58)	(0.39)	(-0.67)	(0.45)	(0.77)	(-0.95)	(-0.31)	(-0.92)	(-2.11)	(-0.69)	(-0.79)
Equity portfolio investment outflow	14.17	-13.67	32.18	21.42	5.19	-32.32	-38.58	-50.29*	-17.35	65.31***	-22.41	-2.19
	(0.50)	(-1.25)	(0.81)	(0.62)	(0.32)	(-1.52)	(-1.05)	(-1.82)	(-0.68)	(3.04)	(-0.96)	(-0.11)
Equity portfolio investment inflow	6.10	-10.05	47.75	3.57	12.13	0.93	35.62	-18.61	-9.94	1.84	8.84	11.12
	(0.27)	(-0.57)	(1.32)	(0.09)	(0.75)	(0.04)	(0.85)	(-0.65)	(-0.34)	(0.07)	(0.32)	(0.41)
Bond portfolio investment outflow	1.36	24.57**	-10.40	18.18	34.21*	-21.42	4.73	0.46	9.77	-15.64	-4.58	23.37
	(0.05)	(2.63)	(-0.47)	(0.61)	(1.93)	(-1.27)	(0.19)	(0.03)	(0.61)	(-1.00)	(-0.34)	(1.42)
Bond portfolio investment inflow	8.40	-1.31	58.89**	29.23	12.57	-1.86	40.23	6.65	-6.27	22.48	-12.39	-1.42
	(0.63)	(-0.14)	(2.38)	(1.44)	(1.54)	(-0.14)	(1.46)	(0.37)	(-0.44)	(1.28)	(-0.80)	(-0.08)
Other investment outflow	-8.41*	2.67	-10.71**	-4.08	-2.95	-7.42**	-0.71	-5.10	-5.07	8.03*	2.05	8.19*
	(-1.87)	(1.16)	(-2.36)	(-0.65)	(-1.15)	(-2.36)	(-0.11)	(-1.47)	(-1.40)	(2.01)	(0.52)	(1.75)
Other investment inflow	1.25	0.84	2.80	7.13	-1.77	2.52	-7.69	2.42	1.22	0.04	1.54	-1.86
	(0.40)	(0.47)	(0.55)	(1.39)	(-0.81)	(0.87)	(-1.42)	(0.52)	(0.42)	(0.01)	(0.52)	(-0.78)
quarter	0.14	0.15	0.58	0.93**	0.07	0.31	0.44	0.60	0.16	0.29	0.65***	0.29
	(0.55)	(0.90)	(1.14)	(2.07)	(0.54)	(1.08)	(1.11)	(1.61)	(0.78)	(1.39)	(3.46)	(1.40)
Constant	-0.56	15.93	-110.76	-165.77*	12.33	-8.20	-53.09	-72.91	12.57	0.35	-96.93**	-17.26
	(-0.01)	(0.49)	(-1.09)	(-1.81)	(0.47)	(-0.15)	(-0.68)	(-0.98)	(0.32)	(0.01)	(-2.66)	(-0.44)
Observations	41	41	41	41	42	42	42	42	43	43	43	43
Adjusted R ²	0.02	0.12	0.57	0.52	0.42	0.03	0.22	0.30	-0.02	0.26	0.17	0.11
F-statistic	2.243	3.908	10.86	14.89	6.431	2.164	1.937	5.372	1.213	3.318	2.758	2.771

Table 7: Cross-border capital flow channels for spillovers and spillbacks

Note: This table reports results of regressions that examine cross-border capital flow channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain quarterly indexes by averaging daily *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

		Bon	d Markets			Stock	Markets		Exchange Rate Markets				
	R	eturn	Vola	ıtility	Re	turn	Vol	atility	Ret	turn	Volat	tility	
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	
PMI export	0.62	-0.96**	-0.76	-2.28***	1.62***	-0.91*	4.29***	0.31	-0.01	-1.36***	0.65	-0.57	
	(1.01)	(-2.12)	(-1.12)	(-2.87)	(3.88)	(-1.87)	(3.15)	(0.60)	(-0.02)	(-2.86)	(1.02)	(-1.21)	
PMI import	-0.81	0.59	1.38	2.12**	-1.64***	0.95	-4.48***	0.29	-0.01	2.37***	-0.23	0.61	
	(-1.07)	(1.02)	(1.65)	(2.10)	(-3.16)	(1.60)	(-2.92)	(0.42)	(-0.02)	(3.88)	(-0.28)	(1.00)	
month	0.01	0.01	0.27***	0.31***	0.10***	0.04*	0.13***	0.15***	0.11***	0.00	0.10***	0.01	
	(0.41)	(0.34)	(6.96)	(10.81)	(5.50)	(1.73)	(3.33)	(6.21)	(5.90)	(0.15)	(4.51)	(0.70)	
Constant	29.47	56.81***	-182.30***	-160.59***	-29.60*	29.83*	-39.77	-77.81***	-26.62**	5.86	-57.07***	24.28	
	(1.61)	(3.59)	(-5.72)	(-5.53)	(-1.81)	(1.68)	(-1.08)	(-3.88)	(-2.14)	(0.33)	(-3.50)	(1.52)	
Observations	133	133	133	133	159	159	158	158	168	168	167	167	
Adjusted R ²	-0.01	0.05	0.33	0.45	0.14	0.06	0.11	0.22	0.18	0.08	0.10	0.00	
F-statistic	0.432	4.207	16.66	51.75	11.43	5.056	6.862	17.76	14.49	6.866	10.39	1.010	

Table 8: Import and export trade channels for spillovers and spillbacks

Note: This table presents results of regressions that examine import and export trade channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain quarterly indexes by averaging daily *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

		Bond M	Iarkets			Stock	Markets		Exchange Rate Markets				
	Ret	turn	Vol	atility	Re	eturn	Vol	atility	R	eturn	Vola	atility	
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	
Household sector	-2.27**	0.58	2.12*	2.45	0.27	0.29	0.74	2.61**	-0.04	1.04	-0.46	-0.91	
	(-2.22)	(0.89)	(1.87)	(1.55)	(0.34)	(0.31)	(0.58)	(2.60)	(-0.07)	(1.56)	(-0.57)	(-1.41)	
NFC sector	1.57**	-0.66	0.13	-0.54	0.53	-0.52	1.52**	-0.65	-0.03	-0.73	0.05	-0.17	
	(2.69)	(-1.54)	(0.15)	(-0.63)	(1.29)	(-1.00)	(2.09)	(-1.02)	(-0.10)	(-1.63)	(0.13)	(-0.45)	
Government sector	-2.04*	-0.43	-0.24	-0.57	-1.39	0.51	-2.93	-0.06	-1.13	-0.55	-1.61	-1.30	
	(-1.90)	(-0.39)	(-0.12)	(-0.27)	(-1.66)	(0.50)	(-1.33)	(-0.05)	(-1.27)	(-0.62)	(-1.56)	(-1.53)	
Financial sector	-1.68***	0.77**	-1.62**	-0.16	-0.38	-0.40	-1.45**	0.47	0.60	0.10	-0.36	0.12	
	(-3.22)	(2.49)	(-2.16)	(-0.19)	(-0.85)	(-0.76)	(-2.09)	(0.65)	(1.63)	(0.20)	(-0.90)	(0.25)	
quarter	1.43*	-0.11	0.62	0.15	-0.07	0.97	-0.49	-0.94	0.03	0.40	1.16**	1.09**	
	(1.74)	(-0.17)	(0.59)	(0.10)	(-0.12)	(1.39)	(-0.42)	(-1.18)	(0.07)	(0.97)	(2.38)	(2.63)	
Constant	-255.01*	108.01	-108.89	15.21	34.01	-86.63	84.97	226.56	48.15	46.82	-135.70*	-105.82	
	(-1.88)	(0.95)	(-0.58)	(0.06)	(0.32)	(-0.71)	(0.45)	(1.61)	(0.82)	(0.63)	(-1.82)	(-1.55)	
Observations	45	45	45	45	53	53	53	53	74	74	74	74	
Adjusted R ²	0.16	0.07	0.59	0.51	0.23	0.17	0.10	0.33	0.25	0.21	0.37	0.31	
F-statistic	2.823	2.098	7.761	19.49	5.685	4.924	3.624	10.57	5.310	9.314	15.66	13.28	

Table 9: Leverage channels for spillovers and spillbacks

Note: This table reports results of regressions that examine leverage channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain quarterly indexes by averaging monthly *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

		Bond	l Markets			Stock	Markets		Exchange Rate Markets				
	Re	turn	Vola	atility	Re	turn	Vola	tility	Re	turn	Vola	tility	
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	
FPU	5.54***	4.95***	0.42	4.14*	-0.26	-0.51	-0.32	-6.17**	1.24	0.51	-3.82*	1.86	
	(3.22)	(3.52)	(0.18)	(1.71)	(-0.15)	(-0.28)	(-0.09)	(-2.50)	(0.70)	(0.26)	(-1.90)	(1.07)	
MPU	-3.92	-2.30	-3.47	-8.27*	-3.62	3.37	-14.53***	2.74	-4.52	2.08	4.53	0.56	
	(-1.40)	(-1.05)	(-1.10)	(-1.90)	(-1.51)	(1.35)	(-3.01)	(0.78)	(-1.62)	(0.78)	(1.48)	(0.20)	
TPU	-1.44***	-0.48	3.86***	1.60**	-0.80*	3.34***	-0.59	2.51***	1.73***	1.09*	-0.11	-1.23*	
	(-2.91)	(-1.35)	(2.97)	(2.09)	(-1.77)	(5.22)	(-0.59)	(3.34)	(2.73)	(1.76)	(-0.15)	(-1.87)	
EXCAPU	-4.19***	-0.82	-7.16***	-3.24*	-0.05	1.07	-1.56	-0.38	4.66*	-1.52	-2.05	-0.70	
	(-3.15)	(-0.51)	(-3.83)	(-1.70)	(-0.03)	(0.67)	(-0.65)	(-0.17)	(1.76)	(-0.64)	(-0.85)	(-0.32)	
month	0.01	0.02	0.17***	0.24***	0.07***	0.03	0.04	0.12***	0.05***	0.05***	0.12***	0.08***	
	(0.17)	(1.27)	(4.55)	(6.94)	(3.62)	(1.47)	(0.90)	(4.81)	(3.62)	(3.51)	(9.42)	(5.64)	
Constant	29.53	23.93*	-78.76***	-119.26***	-5.98	28.04**	31.18	-22.64	7.42	23.12***	-44.14***	-15.05**	
	(1.42)	(1.78)	(-3.35)	(-5.01)	(-0.51)	(2.28)	(1.01)	(-1.54)	(1.06)	(3.19)	(-6.56)	(-2.11)	
Observations	133	133	133	133	159	159	158	158	222	222	216	216	
Adjusted R ²	0.15	0.06	0.47	0.48	0.12	0.20	0.20	0.26	0.16	0.09	0.29	0.18	
F-statistic	6.075	2.978	17.08	55.14	6.862	10.88	10.67	18.18	8.786	8.914	23.55	12.63	

Table 10: Economic policy uncertainty (EPU) channels for spillovers and spillbacks

Note: This table reports results of regressions that examine economic policy uncertainty channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain monthly indexes by averaging daily *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	Bond Markets					Stock	Markets		Exchange Rate Markets			
	R	eturn	Vola	tility	Re	turn	Vol	atility	Ret	urn	Vola	tility
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill
Currency_risk	0.94	-2.29**	1.74	0.40	-1.98**	2.74***	-5.45***	-0.40	1.38*	-1.40*	-3.57***	-2.44***
	(0.70)	(-2.38)	(1.63)	(0.27)	(-2.54)	(3.18)	(-3.10)	(-0.42)	(1.69)	(-1.97)	(-4.05)	(-3.11)
Sovereign_Debt_risk	1.73	2.05**	0.98	3.55**	2.39***	-1.45**	6.70***	-1.09	-0.27	1.13**	0.70	-0.20
	(1.33)	(2.55)	(0.84)	(2.39)	(3.49)	(-2.27)	(3.16)	(-1.28)	(-0.45)	(2.24)	(1.26)	(-0.39)
Banking_risk	-0.90	1.91***	-3.34***	-3.11**	0.49	-1.99**	0.50	-1.19	-2.19***	2.69***	0.96*	1.61***
	(-1.03)	(2.67)	(-3.81)	(-2.61)	(0.54)	(-2.59)	(0.34)	(-1.12)	(-4.12)	(6.44)	(1.96)	(3.45)
Political_risk	-5.29**	3.96***	-0.12	3.73	-1.81	3.90	-7.17	9.33***	-0.84	-0.14	-1.75***	-0.69
	(-2.05)	(3.74)	(-0.02)	(0.99)	(-0.94)	(1.32)	(-0.91)	(3.44)	(-1.27)	(-0.26)	(-2.88)	(-1.15)
Economic_Structure_risk	0.92	-0.22	-1.70*	-0.93	-0.81*	-1.22**	-1.01	-1.71***	-0.47	-1.39***	-0.77	-0.27
	(1.46)	(-0.58)	(-1.72)	(-1.04)	(-1.67)	(-2.18)	(-0.90)	(-2.91)	(-0.83)	(-2.74)	(-1.38)	(-0.70)
month	-0.10	0.03	-0.08	-0.12	0.04	-0.09*	-0.03	0.05	-0.05	0.07**	0.11***	0.09***
	(-1.49)	(0.65)	(-1.39)	(-1.39)	(0.63)	(-1.83)	(-0.39)	(0.69)	(-1.60)	(2.59)	(4.10)	(2.98)
Constant	302.60*	-270.02***	199.13	-49.90	96.52	-13.46	422.76	-322.87**	203.61***	-65.27	139.02**	35.09
	(1.96)	(-3.71)	(0.57)	(-0.24)	(0.94)	(-0.08)	(1.13)	(-2.18)	(4.38)	(-1.12)	(2.53)	(0.57)
Observations	109	109	109	109	135	135	134	134	198	198	192	192
Adjusted R ²	0.06	0.06	0.24	0.29	0.09	0.21	0.20	0.16	0.18	0.25	0.34	0.28
F-statistic	1.688	22.27	3.951	13.85	4.315	5.886	5.628	5.288	9.714	17.11	21.59	27.11

Table 11: Country risk channels for spillovers and spillbacks

Note: This table reports results of regressions that examine country risk channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain monthly indexes by averaging daily *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

		Bond	l Markets			Stock	Markets		Exchange Rate Markets			
	Ret	urn	Vola	tility	Reti	ırn	Vola	tility	Re	turn	Vola	tility
Variables	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill	tospill	fromspill
CFRI	0.74	0.83	-3.20***	-4.25***	-1.43*	-1.00	0.85	0.26	-0.86	-2.35**	4.00***	2.64**
	(0.76)	(1.33)	(-3.34)	(-3.69)	(-1.80)	(-1.35)	(0.69)	(0.28)	(-0.96)	(-2.28)	(3.88)	(2.43)
month	-0.04	-0.01	0.29***	0.34***	0.11***	0.03	0.22***	0.25***	0.08***	0.08***	0.13***	0.05*
	(-1.46)	(-0.62)	(6.78)	(10.12)	(5.50)	(1.29)	(5.48)	(10.38)	(3.52)	(3.63)	(4.96)	(1.88)
Constant	52.08***	49.37***	-168.69***	-187.41***	-36.52***	36.27**	-110.83***	-110.74***	-12.15	2.15	-52.03***	0.53
	(3.07)	(4.08)	(-6.26)	(-8.81)	(-3.00)	(2.26)	(-4.32)	(-7.38)	(-0.80)	(0.15)	(-3.18)	(0.03)
Observations	124	124	124	124	124	124	123	123	124	124	124	124
Adjusted R ²	0.01	-0.00	0.34	0.44	0.16	0.01	0.20	0.40	0.06	0.09	0.24	0.07
F-statistic	2.197	1.030	27.37	56.29	15.17	1.573	15.15	63.51	6.217	7.215	27.62	6.590

Table 12: Financial condition channels for spillovers and spillbacks

Note: This table presents results of regressions that examine financial condition channels for spillovers and spillbacks (*Fromspill* and *Tospill*). Robust standard errors are reported in parentheses. We obtain monthly indexes by averaging daily *Fromspill* and *Tospill*. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

Figure 1. Total spillovers for bond, stock, and foreign exchange markets

Note: This figure shows the total spillover indexes (*Totalspill*) for bond, stock, and foreign exchange markets, respectively. The title of each graph represents different types of spillovers for different markets. For instance, Bond Market Returns indicates that we use the 10-year government bond return for each country to measure the degree of total return spillovers of bond markets (China+G7), while Bond Market Volatility indicates that we use the volatility of government bond return for each country to measure the degree of total volatility spillovers of bond markets (China+G7). The horizontal axis for each graph is the date. For example, 2000w1 is the first week of 2000. The vertical axis of each graph is the *Totalspill* index. The horizontal red line is the average *Totalspill* for each market during the sample period. The two shaded bars in each graph are the periods of financial crises. GFC denotes the 2008 global financial crisis, and EDC denotes the period of the European debt crisis.



Note: This figure a spinlotenes for bond, store, and foreign exchange markets (from change markets, respectively. The title of each graph represents different types of spillbacks for different markets. For instance, Bond Market Returns (CN \rightarrow) indicates that we use the 10-year government bond return for each country to measure the degree of spillbacks from China to the G7, while Bond Market Volatility (CN \rightarrow) indicates that we use the volatility of government bond return for each country to measure the degree of volatility spillbacks of bond markets from China to the G7.



Note: This figure shows the spillover indexes (*Fromspill*) for bond, stock and foreign exchange markets, respectively. (1) The title of each graph represents different types of spillovers for different markets. For instance, Bond Market Returns (\rightarrow CN) indicates that we use the 10-year government bond return for each country to measure the degree of return spillovers from the G7 to China, while Bond Market Volatility (\rightarrow CN) indicates that we use the volatility of government bond return for each country to measure the degree of volatility spillbacks of bond markets from the G7 to China.



Note: This figure 4. Net spinbacks for bond, stock, and foreign exchange markets (from China to G7 countries) Note: This figure shows the net spillback indexes (*Netspill*), which is equal to *Tospill* minus *Fromspill*, for bond, stock, and foreign exchange markets, respectively. The title of each graph represents different types of net spillbacks for different markets. For instance, Bond Market Returns ($CN \rightarrow minus \rightarrow CN$) indicates that we use the 10-year government bond return for each country to measure the degree of net spillbacks from China to the G7, while Bond Market Volatility ($CN \rightarrow minus \rightarrow CN$) indicates that we use the volatility of government bond return for each country to measure the degree of net volatility spillbacks of bond markets from China to the G7.



Note: This figure shows the pairwise spillover indexes (*Pairspill*) for bond markets from China to the G7 countries. The legend of each graph represents different types of pairwise spillovers between different markets. For instance, $CN \rightarrow US$ (Ret) indicates that we use the 10-year government bond return to measure the degree of pairwise return spillovers from China to US, while $CN \rightarrow US$ (Vol) indicates that we use the volatility of government bond return for each country to measure the degree of pairwise volatility spillbacks of bond markets from China to US. The horizontal axis of each graph is the date. For example, 2000m1 represents the first month of 2000. The vertical axis of each graph represents *Pairspill*. US, UK, JP, GE, FR, IT, CA, and CN represent the

United States, the United Kingdom, Japan, Germany, France, Italy, Canada, and China, respectively.



Note: This figure shows the pairwise spillover indexes (*Pairspill*) for stock markets from China to the G7 countries. The legend of each graph represents different types of pairwise spillovers between different markets. For instance, $CN \rightarrow US$ (Ret) indicates that we use the stock market returns to measure the degree of pairwise return spillovers from China to US, while $CN \rightarrow US$ (Vol) indicates that we use the volatility of government bond return for each country to measure the degree of pairwise volatility spillbacks of stock markets from China to US.



Figure 7. Pairwise spillovers between the Chinese and G7 foreign exchange markets

Note: This figure shows the pairwise spillover indexes (*Pairspill*) for foreign exchange markets from China to the G7 countries. The legend of each graph represents different types of pairwise spillovers between different markets. For instance, $CN \rightarrow US$ (Ret) indicates that we use the currency returns to measure the degree of pairwise return spillovers from the Chinese RMB to US dollar, while $CN \rightarrow US$ (Vol) indicates that we use the volatility of government bond return for each country to measure the degree of pairwise volatility spillbacks of stock markets from the Chinese RMB to US dollar. US, UK, JP, EU, CA, and CN represent the United States, the United Kingdom, Japan, Eurozone, Canada, and China, respectively.



Figure 8. Generalized impulse response analysis for bond markets

Note: This figure shows the generalized impulse response Chinese and G7 bond markets. The legend of each graph represents the generalized impulse response from China to other countries. For example, $CN \rightarrow US$ (Ret) indicates that we use bond market returns to measure the response of the US bond markets return under a one-standard-deviation shock to an orthogonalized innovation of Chinese bond market return, while US \rightarrow CN (Ret) indicates that we use bond market returns to measure the response of Chinese bond markets return under a unit shock to an orthogonalized innovation of the US bond markets return. $CN \rightarrow US$ (Vol) indicates that we use the volatility of bond market to measure the response of the US bond market volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese bond market volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese bond market volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese bond market volatility, while US \rightarrow CN (Vol) indicates that we use the volatility of bond market to measure the response of China's bond markets volatility under a one-standard-deviation shock to an orthogonalized innovation of the US bond markets volatility. The horizontal axis of each graph represents forecast period (from 1 week to 10 weeks). The vertical axis of each graph is response results. The horizontal red line is when response results equal zero. US, UK, JP, GE, FR, IT, CA, and CN represent the United States, the United Kingdom, Japan, Germany, France, Italy, Canada, and China, respectively.



Figure 9. Generalized impulse response analysis for stock markets

Note: This figure shows the generalized impulse response between Chinese and G7 stock markets. The legend of each graph represents the generalized impulse response from China to other countries. For example, $CN \rightarrow US$ (Ret) indicates that we use stock market returns to measure the response of the US stock markets return under a one-standard-deviation shock to an orthogonalized innovation of Chinese stock markets return, while US \rightarrow CN (Ret) indicates that we use stock market returns to measure the response of Chinese stock markets return under a one-standard-deviation shock to an orthogonalized innovation of the US stock markets return. $CN \rightarrow US$ (Vol) indicates that we use the volatility of stock market to measure the response of the US stock market volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese stock market volatility, while US \rightarrow CN (Vol) indicates that we use the volatility of stock market to measure the response of the US stock market volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese stock market volatility, while US \rightarrow CN (Vol) indicates that we use the volatility of stock market to measure the response of China's stock markets volatility under a one-standard-deviation shock to an orthogonalized innovation of the US stock markets volatility.



Figure 10. Generalized impulse response analysis for foreign exchange markets

Note: This figure shows the generalized impulse response between Chinese and G7 foreign exchange markets. The legend of each graph represents the generalized impulse response from China to other countries. For example, $CN \rightarrow US$ (Ret) indicates that we use currency returns to measure the response of the US currency return under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency return, while US $\rightarrow CN$ (Ret) indicates that we use currency returns to measure the response of Chinese currency return under a one-standard-deviation shock to an orthogonalized innovation of the US currency return. $CN \rightarrow US$ (Vol) indicates that we use the volatility of currency returns to measure the response of the US currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of Chinese currency volatility under a one-standard-deviation shock to an orthogonalized innovation of the US currency volatility.