We use the DFM approach in our characterization of the financial cycle. The first step is to select the appropriate variables for measuring the financial cycle. In the second step, DFM is used to extract the dynamic common factors in the selected variables. In the third step, the financial cycle is obtained by filtering the dynamic common factors using a Hodrick-Prescott (HP) filter.

Table 2. Database and countries list.

Variable	Variable Definition	Source
Equity Price	Share Price (Index) deflated using the Consumer Price Index (CPI)	IFS
Credit scale	Domestic credit to private sector (% of GDP) deflated using CPI	WB
Housing Prices	Nominal housing prices deflated using CPI	OECD, National Bureau of Statistics
Interest rate	Lending rate deflated using CPI	IFS, WB
Exchange rate	Nominal exchange rate deflated using CPI	IFS
Sample countries: China (CHN), United States (US), United Kingdom (UK), Germany (GER), France (FRA), and Japan (JPN).		

Note: The interest rate is deposit interest rate deflated using CPI in France, government 10-year bonds interest rate deflated using CPI in Germany, and lending interest rate deflated using CPI in others. Regarding the sample countries, we have done a lot of work on data collection and model fitting. When choosing a sample country for a developed country, our initial consideration was the G7 (United States, United Kingdom, Germany, France, Japan, Italy and Canada). The choice of the G7 equity markets is quite natural given their importance in the global economy, with these countries representing nearly two-third of global net wealth, and nearly half of world output (Ji et al., 2018). But the financial cycles of Italy and Canada are characterized by strong collinearity with other countries when fitting the VAR. As a result, we generated a singular matrix in the financial cycle when calculating VAR, and the financial cycle matrix cannot converge. With the applicability and availability of the data, we finally determined the samples from developed countries such as the United States, United Kingdom, Germany, France, and Japan. IFS denotes International Financial Statistics; IFS denotes World Bank; OECD denotes Organization for Economic Co-operation and Development.

First, we discuss the variables of the credit and financial asset prices that its volatility can reflect the cyclical fluctuations of the financial cycle. We provide additional information about the sample countries, variables in the dataset, and their sources in Table 2. We study financial cycles in five distinct but interdependent variables of credit and financial asset price: equity price, credit scale, house price, interest rate and exchange rate.

Equity prices: Changes in the equity price are highly correlated with changes in corporate capital and affect corporate investment and spending. Equity price affects the accumulation of wealth through various channels, thus affecting consumption. Based on this, equity price is one of the most important variables for measuring the financial cycle.

Credit scale: Credit is a natural aggregate used to analyze financial cycles as it constitutes the single most important link between savings and investment (Claessens et al., 2012). Our measure of credit is aggregate claims on domestic credit to the private sector (% of GDP). Many studies directly use credit or the ratio of credit to GDP to represent the financial cycle.

Housing prices: Fluctuations in housing prices have created huge financial risks. For example, the bankruptcy of Fannie Mae and Freddie Mac which perform an important role in the US housing finance system triggered the Great Recession in 2008. So, we have to consider housing prices, measuring the condition of the financial market or financial cycle.

Exchange rate: From the perspective of international competition, an appreciation or depreciation in the exchange rate can affect the price of goods and labor in the country and thus affect other countries. For instance, many countries are restoring price competitiveness via exchange rate devaluation (Comunale & Hessel, 2014). Therefore, we use the exchange rate as a representative indicator of financial asset prices.

Interest rate: The main determinant of a firm's cost of capital and the decisive factor in a firm's financing and investment is the interest rate. When we measure the financial cycle, we need to consider current interest rates and their trends.

Second, we construct DFM with time-varying parameters and stochastic volatility, following Engle (1993) and Del Negro and Otrok (2008).

We describe five variables, a six-country data panel FC_t, spanning a cross section of N series, and an observation period of time T with a one-factor model and time-varying factor loadings. The observation equation is

$$FC_t = \Lambda_t f_t + U_t, \tag{1}$$

where f_t represents a latent factor, while Λ_t is a $N \times 1$ coefficient vector linking the common factor to the ith variable at time t, and U_t is an $N \times 1$ vector of variable-specific idiosyncratic components. The latent factor captures the common dynamics of the dataset and is the primary focus of interest here. We assume that the factor evolves according to an AR (q) process:

$$f_t = \varphi_1 f_{t-1} + \cdots + \varphi_q f_{t-q} + \upsilon_t, \tag{2}$$

with $\upsilon_t = e^{h_t} \xi_t$ and $\xi_t \sim N(0,1)$. The log volatility h_t follows a random walk without drift:

$$h_t = h_{t-1} + \eta_t, \tag{3}$$

where $\eta_t \sim N\left(0, \sigma_\eta^2\right)$.

The idiosyncratic components U_t are assumed to follow an AR (p) process:

$$U_t = \Theta_1 U_{t-1} + \cdots + \Theta_p U_{t-p} + \chi_t, \tag{4}$$

where $\Theta_1, \cdots, \Theta_p$ are $N \times N$ diagonal matrices and $\chi_t \sim N\left(0_{N\times 1}, \Omega_\chi\right)$ with

$$\Omega_{\chi} = \begin{bmatrix} \sigma_{1,\chi}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,\chi}^2 & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{N,\chi}^2 \end{bmatrix}.$$

Through the steps outlined here, we extract the time-varying common factor of the financial cycle of each sample country from the five variables.

Third, we obtain the cyclical term of the time-varying common factor mentioned above using an HP filter. We regard the cyclical term of each country's common factor as the financial cycle.

3.2. Spillover index

In this section, we construct a spillover index and its derivatives, following the settings in the DY spillover index (Diebold & Yilmaz, 2012). Let x_t be a covariance stationary variable of dimension N that obeys a vector autoregressive model:

$$x_t = \sum_{i=1}^{P} \Phi_i x_{t-i} + \varepsilon_t, \tag{5}$$

where ε_t is an independent and identically distributed vector of size N that follows a Gaussian distribution with a zero mean and a variance matrix denoted Σ. Its moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices A_i obey the equation:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}, \tag{6}$$

with A_0 an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. This representation is usually used to perform an impulse response analysis or a forecasting variance decomposition. In both cases, their use aims to clarify how the estimated system works: how shocks ε_t spread from the i^{th} element of the system to the others sequentially. Variance decompositions allow us to assess the share of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $j \neq i$, for each.

The covariance matrix of ε_t is usually nondiagonal, thus Diebold and Yilmaz propose using a generalized VAR framework, which produces variance decomposition is not affected by ordering, hereafter KPPS[2] (Koop, Pesaran, & Potter, 1996; Pesaran & Shin, 1998).

We follow Diebold and Yilmaz's methodology. Denoting the generalized H-step-ahead forecast error variance decompositions by $\theta_{ij}(H)$, for $H = 1, 2, \cdots,$ we obtain

2 More details can refer to Diebold & Yilmaz, 2012.

$$\theta_{ij}(H)=\frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_j\right)}, \tag{7}$$

Unlike the decompositions obtained through Cholesky factorization, generalized H -step-ahead forecast error variance decompositions do not have to sum to one, and in general they do not

$$\sum_{j=1}^{N}\theta_{ij}(H)\neq 1.$$

To normalize the variance decompositions obtained from the generalized approach, we sum all (own and spillover of shocks) contributions to a country's financial cycle forecast error. When we divide each source of financial cycle shock by total financial cycle contributions, we obtain the relative contributions to each country by itself and other countries:

$$\tilde{\theta}_{ij}(H)=\frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)}, \tag{8}$$

Now, by construction $\sum_{j=1}^{N}\tilde{\theta}_{ij}(H)=1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)=N$.

Total Spillovers: Using the contributions from the generalized variance decomposition approach, we can construct a total financial cycle spillover index:

$$TS(H)=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)}\times 100=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}(H)}{N}\times 100. \tag{9}$$

Directional Spillover: We only consider directional spillovers here. We measure directional spillover transmitted by country i to all other countries j, and directional spillover received by country i from all other countries j as

$$DS_{i\rightarrow}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ji}(H)}\times 100 \quad \text{and} \quad DS_{i\leftarrow}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}(H)}\times 100. \tag{10}$$

Net Spillovers: Finally, we obtain the net financial cycle spillovers transmitted from country i to all other countries as

$$NS_i\left(H\right)=DS_{i\to}\left(H\right)-DS_{i\leftarrow}\left(H\right). \tag{11}$$

Net spillovers are simply the difference between gross financial cycle shocks transmitted to and gross financial cycle shocks received from all other countries.

3.3. Markov-switching autoregressive model

The Markov-switching autoregressive model does not have to artificially set thresholds to determine the switching regimes, nor does it need to predict the time of regime switching. It determines the regimes by the smooth transition of state variables between different states. This nonlinear framework, a Markov model, captures the dynamics of smooth transition through the regime transition variables (Li et al., 2018; Broni and Masih, 2019).

Let Chinese financial cycle net spillovers, NS_t, be a stationary time series of $T+p$ observations whose autoregressive dynamics evolve according to an unobservable K-state Markov-chain process s_t. General characterizations of stationarity conditions for such processes can be found in Francq and Zakoïan (2001). For the sake of generality, the means, regression coefficients, and volatility of the Markov-switching autoregressive model are state dependent:

$$NS_t=\mu_{s_t}+\sum_{j=1}^{p}\phi_{j,s_{t-j}}\left(NS_{t-j}-\mu_{s_{t-j}}\right)+\varepsilon_t, \tag{12}$$

where $\varepsilon_t \sim N\left(0,\sigma^2\right)$ and p is the lag length of the underlying state-dependent autoregressive process of financial cycle spillovers. Following the standard assumptions on Markov-switching autoregressive models, we focus on normal errors. However, this is not restrictive and can easily be generalized. To complete the statistical characterization of this process, we assume that s_t is a Markov chain of order 1. Then, the probability of a change in regime depends on the past only through the value of the most recent regime:

$$\begin{aligned}&P\left(s_t=j\mid s_{t-1}=i,\cdots,s_1=l,Y_{t-1}\right)\\&=P\left(s_t=j\mid s_{t-1}=i\right)=p_{ij},\end{aligned} \tag{13}$$

where $Y_t=NS_1,NS_2,\cdots,NS_t$, and $i,j=0,1,\cdots,K-1$.

Because the nonlinear autoregressive process depends not only on s_t but also on $s_{t-1},\cdots,s_{t-p}$, it is convenient to define the latent variable $s_t^*=\left(s_t,s_{t-1},\cdots,s_{t-p}\right)$, which results in K^{p+1} different states. The transition probabilities of s_t^* can easily be found from the transition probabilities of the primitive states s_t. Let us define the states j of s_t^* as $\mathrm{j}=\left(j_0,j_1,\cdots,j_p\right)$, with $j_i\in\{0,1,\cdots,K-1\}$, $i=0,1,\cdots,p$. Then, the transition probabilities of s_t^* are

$$P\left(s_t^* = \mathrm{j} \mid s_{t-1}^* = \mathrm{i}\right) := p_{\mathrm{ij}}^* \\ = \begin{cases} p_{i_0 j_0} & \text{always } i_r = j_{r-1} \text{ for } r = 1, 2, \ldots, p \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

4. Chinese financial cycle spillovers

4.1. Data description

We measure the financial cycles of the sample countries based on the variables and methods mentioned above. All macroeconomic and financial variables we use have quarterly frequency. The data coverage is January 1990–April 2017, beginning in January 1990 because Chinese financial variable data are lacking before then. Specifically, in the process of measuring the financial period, we next specifically explain some data preprocessing. Some of the missing data were estimated by constructing an OLS regression equation. We used the quadratic-match averaging method to convert credit-scale data from annual frequency to quarterly frequency. Other indicators in the study can be obtained directly. Statistical information such as maximum, minimum, average, standard deviation, skewness, and kurtosis values of the variables involved are in Table 3. The corresponding model is constructed for financial cycle spillovers by measuring the financial cycle for the sample countries.

4.2. Chinese financial cycle spillovers general analysis

We next explore the characteristics of Chinese financial cycle general spillover. Using these financial cycle series, we estimate the VAR model presented in Equation (5), selecting the lag using the Akaike information criterion (2 lags here). Using these estimations, we compute the given spillover as in Equation (10). In a four-quarter ahead forecasting horizon (H) for variance decomposition is used to construct the spillover table. To analyze the results more intuitively, we normalized the directional spillover index obtained, which indicated that we should set the directional spillover index (including own) at 100%. All these results are presented in Table 4.

Table 3. Descriptive statistics of sample countries.

Variable	Country	Statistics						
		Mean	Median	Max.	Min.	Std.	Skew.	Kurt.
Equity Price	CHN	0.700	0.684	2.012	0.103	0.337	0.873	5.139
	US	1.034	1.096	1.875	0.387	0.357	−0.149	2.411
	UK	0.995	1.016	1.352	0.563	0.210	−0.333	2.061
	GER	1.051	1.048	1.733	0.552	0.318	0.256	1.931
	FRA	1.067	1.033	2.064	0.595	0.340	0.720	3.144
	JPN	1.490	1.468	3.115	0.836	0.406	0.782	4.626
Credit scale	CHN	0.609	0.579	1.083	0.358	0.208	0.552	2.087
	US	0.862	0.841	1.108	0.728	0.115	0.597	2.219
	UK	0.685	0.794	1.024	0.370	0.227	−0.169	1.405
	GER	0.957	0.953	1.094	0.824	0.086	0.067	1.632
	FRA	0.781	0.764	1.076	0.500	0.210	0.006	1.243
	JPN	1.224	1.113	1.805	0.923	0.279	0.586	1.935
Housing Prices	CHN	1.392	1.319	2.205	1.025	0.293	1.556	4.408
	US	1.644	1.645	2.083	1.211	0.225	−0.335	2.755
	UK	1.923	1.886	2.363	1.644	0.203	0.452	1.895
	GER	2.107	2.058	2.853	1.460	0.466	0.047	1.495
	FRA	1.026	0.994	1.322	0.889	0.115	1.295	3.778
	JPN	0.979	0.978	1.171	0.744	0.139	−0.242	1.805
Interest rate	CHN	0.095	0.070	0.250	0.036	0.058	1.220	3.153
	US	0.075	0.074	0.171	0.030	0.040	0.406	2.073
	UK	0.058	0.054	0.247	0.004	0.054	1.460	5.546
	GER	0.051	0.045	0.131	−0.001	0.034	0.574	2.709
	FRA	0.033	0.031	0.064	0.007	0.017	0.327	2.018
	JPN	0.025	0.018	0.080	0.010	0.018	1.777	5.036
Exchange rate	CHN	1.330	1.049	3.754	0.936	0.698	2.266	6.726
	US	1.241	1.280	1.592	0.901	0.215	−0.061	1.632
	UK	1.328	1.416	1.982	0.820	0.294	−0.053	2.144
	GER	1.078	1.057	1.338	0.887	0.118	0.331	2.273
	FRA	1.086	1.057	1.307	0.894	0.121	0.221	1.875
	JPN	0.814	0.815	1.106	0.488	0.131	−0.175	3.305

Table 4. Spillovers table for financial cycle of the sample countries.

	CHN	US	UK	GER	FRA	JPN
CHN	89.63	4.45	0.82	2.05	0.14	2.91
US	5.95	89.01	1.49	0.07	3.48	0.00
UK	2.89	0.55	84.24	0.17	4.53	7.62
GER	5.62	0.33	10.98	81.79	0.09	1.19
FRA	11.20	0.02	1.33	1.32	85.85	0.28
JPN	4.96	0.80	13.65	3.86	1.49	75.24
Directional TO others	30.62	6.15	28.27	7.47	9.73	12.00

Table 4 shows three interesting results. First, Chinese financial cycle directional spillovers have significant differences. The financial cycle spillovers from China are 11.20 to France, 5.95 to the United States, 5.62 to Germany, 4.96 to Japan, and 2.89 to the United Kingdom. The Chinese financial cycle has a great contribution (30.62) to developed countries. Financial cycle shocks originating from China are more likely to be transmitted to developed countries than internal digestion. This effect is very similar to UK, where 28.27 contribution is transmitted to other countries, while 84.24 to be contained within own borders. Second, the Chinese financial cycle directional spillovers exceed the average developed countries' spillover. Specifically, the mean of developed countries' financial cycle directional spillovers to others is 12.72. The shocks originating in China can also be a good indicator of future changes in developed countries' financial cycles. Third, the Chinese financial cycle directional spillovers are relatively unbalanced than those of most developed countries. China has the lowest standard deviation of financial cycle directional spillovers, a total of 2.75. We use the same method to calculate the standard deviation. The United Kingdom has the maximum variance of financial cycle directional spillovers (5.51), followed by Japan (2.80), France (1.79), the United States (1.63), and Germany (1.39).

4.3. Chinese financial cycle net spillovers specific events analysis

Table 4 does not show many time-varying features, but we are still committed to further examining Chinese financial cycle net spillovers time-varying features over certain periods. We performed a rolling estimation of financial cycle spillovers using 20-quarter rolling windows (a time equivalent to five years) to analyze potential time variations. Using these estimations, we compute the given spillover as in Equations (10) and (11) with 20-quarter rolling windows. The Chinese net spillover index is presented in Figure 1.

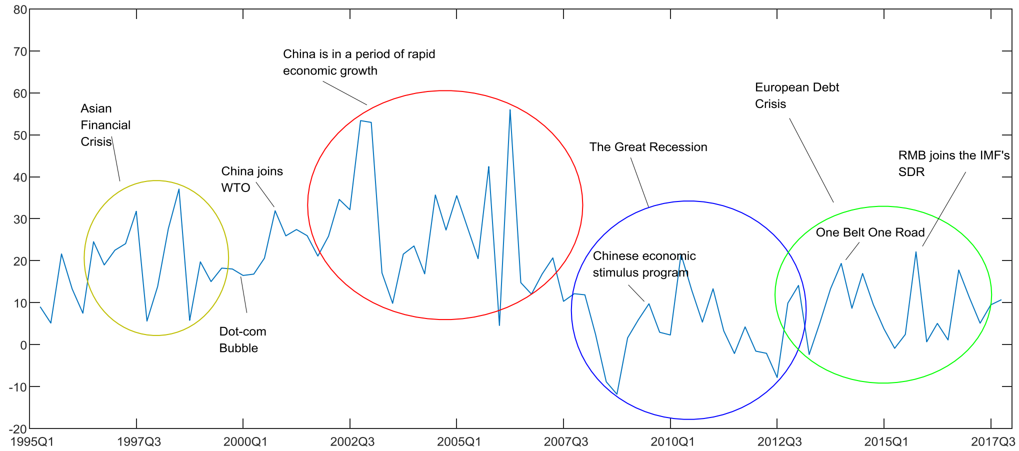

Figure 1. Financial cycle net spillovers from China to developed countries. Note: VAR lag used in the estimation is 2, step of forecasting horizon is 4 quarters, and rolling-window length is 20 quarters.

Figure 1 shows the time-varying financial cycle net spillovers from China to developed countries. As seen in Figure 1, the Chinese financial cycle net spillover index value is normally around 5–15; however, during certain periods, the spillover increases to as much as 56.0 or decreases to as little as −11.8. Large variability in the net spillovers index is present, and the index is very sensitive to specific events. Combined with its fluctuation and special events, we can roughly divide the net spillovers index over the period from 1995Q1 to 2017Q4 into several cycle[3].

The first cycle began in 1995Q1 and ended in 1999Q4, showing the instability in the Chinese financial cycle net spillover index. In this cycle, Chinese financial cycle net spillovers fluctuate between 5.1 in 1995Q3 and 37.1 in 1998Q3. A specific event that occurred during this period was the Asian financial crisis. Through free exchange transactions in various regions of Asia, George Soros, an investor, has caused currency depreciation in Southeast Asian countries. The renminbi is still cannot be freely exchanged. Devaluation of the renminbi has stabilized the Chinese economy. Because of this crisis, Chinese financial cycle net spillover suffered a disruption.

The second cycle started in 2000Q1 and ended in 2007Q3, during which Chinese financial cycle net spillovers gradually increased. In this cycle, the Chinese financial cycle net spillover index value is normally around 20–50. Specifically, China became a member of the World Trade Organization on December 11, 2001, which signified China's deeper integration into the world economy (Hasmath & Hsu, 2007). The effects from Chinese financial cycle spillovers are expected to be gradual not only because China has opened up its economic market but also because it became a world economic power based on a sound set of economic and financial fundamentals (Filardo et al., 2010). During this period, China's stocks experienced a big bull market. For example, the CSI 300 index increased 474%, from 940 at the beginning of 2006 to more than 5,400 in June 2007.

The third cycle started in 2007Q4 and ended in 2013Q3, when Chinese financial cycle net spillovers went through a trough. In this cycle, the lowest value of Chinese financial cycle net spillovers fell to −11.8 in 2008Q4, most importantly because the US subprime mortgage crisis dealt

[3] When we calculate the rolling-window regression of the spillover index, we use the data for 1990Q1–1994Q4, that is, the 20-quarter (five years) as the window length. So, the spillover index omits the data for 1990Q1–1994Q4.

a huge blow to the global economy. To minimize the influence from an external shock, in 2008–2009 the Chinese government put into effect an economic stimulus program, totaling RMB 4 trillion. Even though the economic stimulus program had a positive effect on China's financial market (it rebounded to 9.7 in 2009Q3), Chinese financial cycle net spillovers remained below normal.

The fourth cycle started in 2013Q4 and ended in 2017Q4, during which Chinese financial cycle net spillovers recovered from the financial crisis. During this stage, the Chinese financial cycle spillover index fluctuates between 0 and 20. When the Belt and Road initiative was proposed, it was expected to affect the Chinese market. Then, the Chinese spillover index began to rise, attaining 19.3 in 2014Q1. When the international economy was shocked from the European debt crisis, the Chinese financial cycle net spillover index continued to fall and fluctuated at a low level. After the internationalization of the renminbi, on November 30, 2015, the IMF voted to make the renminbi a world currency and including it in the basket of SDRs. In 2015Q4, Chinese financial cycle net spillovers rose to 22.1 the maximum value in the fourth cycle.

The spillover index has a large range of fluctuations, and the difference between the maximum and minimum is as high as 67.8. Therefore, one of the essential conclusions of this article is that Chinese financial cycle net spillovers have significant time-varying feature which has a strong correlation with specific events. To describe the overall characteristics of China's financial cycle spillovers to different countries, we trace the net spillovers of China's financial cycle to each developed country, as shown in Figure 2.

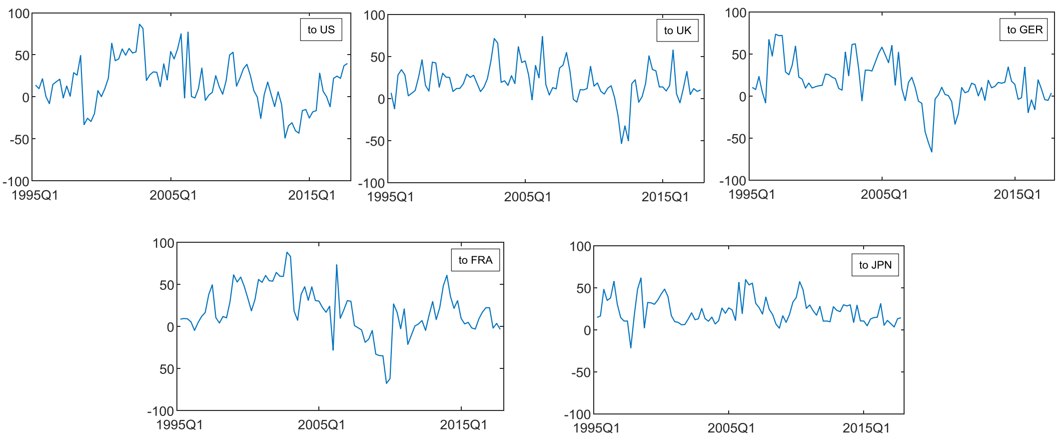

Figure 2. Financial cycle net spillovers from China to developed countries. Note: VAR lag used in the estimation is 2, step of forecasting horizon is 4 quarters, and rolling-window length is 20 quarters.

Figure 2 shows the financial cycle net spillovers from China to the developed countries, and the trends are largely consistent with those in the index in Figure 1. A closer look reveals that value of financial cycle net spillovers from China is slightly higher to the United States than to other developed countries and lower to Japan. The results in Figure 2 are consistent with our conclusions in Table 4. This further proves a significant difference on financial cycle spillovers from China to developed countries, which is consistent with expectations.

4.4. Robustness test

We now perform some simple variations on our basic analysis to check robustness with respect to the rolling-window length and the forecast horizon.

Using a rolling-window length of 28 quarters and 36 quarters and two different variance decomposition forecast horizons, with 8-quarter and 12-quarter horizons, our results remain robust.

The results appear largely robust to variation in window length and forecast horizon. Chinese financial cycle spillover index for the 28-quarter and 36-quarter rolling window is more stable over time because it uses more observations but is generally similar to the 20-quarter rolling window length. The Chinese financial cycle variance spillover index matrix may change if the forecast horizon (H) is too small. When is larger, the matrix converges quickly to a stable value, which is consistent with findings of Diebold and Yilmaz (2009).

5. Chinese financial cycle net spillovers regime switching

In this section, we highlight the different regimes in Chinese financial cycle net spillovers. The Chinese financial cycle net spillover index shows the nonlinear and asymmetrical features mentioned above, which we analyze using a Markov-switching autoregressive (MS-AR) model. We also conduct a unit-root test to further investigate the Chinese financial cycle net spillover, the adjusted Dickey-Fuller (ADF) test. Before the conducting the test, we need to determine whether the net spillover series of Chinese financial cycles has a trend item or an intercept item. Figure 1 shows both trend and intercept items, and the test results are in Table 5, indicating that the ADF statistic is −6.505 (< −4.063), with a p-value of 0.000. We believe that the net spillover series in the Chinese financial cycle is significantly stationary.

Table 5. ADF test results of China's financial cycle net spillover.

Variable	Test critical values:			ADF test statistic	Prob.
	1% level	5% level	10% level		
NS_t	−4.063	−3.461	−3.156	−6.505	0.000

Next, we need to determine the number of regimes and the lag order of the MS-AR model, and we do so using the log-likelihood value. Specifically, we select regimes 2–6 and lag orders 1–5 in the MS-AR model to calculate the log-likelihood values for different cases. The results show[4] if the lag order is held constant, the log-likelihood value tends to be stable with more than three regimes, and is not sensitive to lag order. Finally, we fit the MS (3)-AR (2) model to the net spillover series of the Chinese financial cycle. As we expected, the three-regime Markov-switching model respectively represent contraction moderation, and expansion regimes.

We calculated the Equation (12) mentioned above. Table 6 shows estimation results for the MS (3)-AR (2) model with coefficients, t value, R-squared, and significance levels.

[4] We compare the log-likelihood values of MS-AR models under different regimes and lag orders. The laws are summarized, but the results of log-likelihood values are omitted here.

Table 6. The parameter estimation of Markov-switching autoregressive model.

Regime	(1)		(2)		(3)	
	Estimate	t value	Estimate	t value	Estimate	t value
μ_{S_t}	-0.072^{**}	-6.093	0.114^{*}	1.942	0.024	1.012
ϕ_1	0.253^{**}	26.103	-0.008	-0.190	0.879^{**}	7.577
ϕ_2	1.497**	66.520	0.022	0.221	0.007	0.032
R^2	0.994		0.002		0.675	

In Table 6, these three regimes are the contraction regime (regime 1, $\mu_{S_t} = -0.072$), expansion regime (regime 2, $\mu_{S_t} = 0.114$), and moderation regime (regime 3, $\mu_{S_t} = 0.024$).

Based on Table 6, we conclude that the effect of lag order on the China's financial cycle net spillover has nonlinear features. In regime 1, the impact of the first- and second-order coefficients on China's financial cycle net spillover are 0.253 and 1.497, which are significant. However, they are not significant in regime 2, −0.008 and 0.022. Only in regime 3 is the first lag significant.

We further investigate the transition probabilities between the three regimes. Using Equation (14), we obtain the transition probabilities matrix in Table 7, from which we draw several results conclusions. First, Chinese financial cycle net spillovers have a high probability of remaining in the same regime. The net spillovers are extremely stable in regime 3, with 72.1%, as well as regime 2, with a probability of 62.2%. Second, the transition probabilities between different regimes vary. For example, the transition probability from regime 3 to regime 1 is only 11.6%, which implies that a moderate net spillover will not shrink at once. In addition, when the initial regime is regime 1, the probability of jumping directly to regime 2 is the highest, likely because of macroeconomic regulation.

Table 7. The transition probabilities matrix of MS-AR model.

	Regime 1	Regime 2	Regime 3
Regime 1	0.217	0.174	0.116
Regime 2	0.393	0.622	0.163
Regime 3	0.390	0.204	0.721

To demonstrate the asymmetry of the spillover, we traced the smoothed and filtered probabilities of net spillovers of Chinese financial cycles, shown in Figure 3. Intuitively, we can see that regime 3 is the most dominant, exceeding 50% in most of the sample period. The probability of regime 1 does not fluctuate frequently, which is consistent with the conclusions we drew from Table 7. Overall, it is a low spillover regime. Regime 2 is not persistent, displaying the highest fluctuation in net spillover. The smoothed probability peaks in this regime correspond to the period in which Chinese financial cycle net spillovers rapidly increase. This is likely to be related to economic policies. So, this regime is changeable.

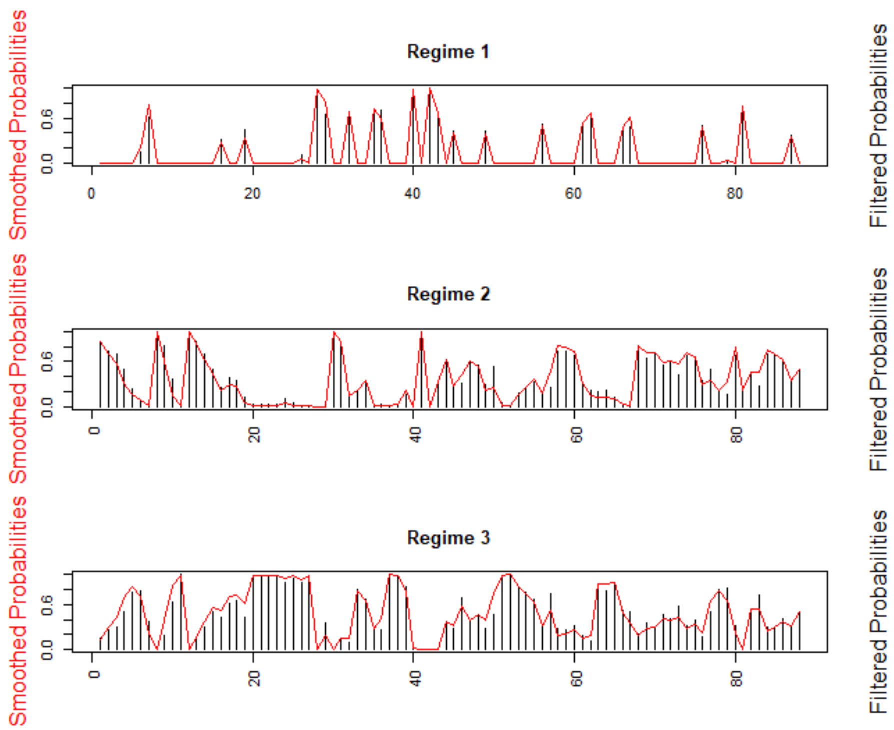

Figure 3. Smoothed and filtered probabilities of net spillovers of Chinese financial cycles.

6. Conclusions

In this paper, we highlight and empirically analyze unidirectional spillovers of the financial cycle from China to developed countries over the period 1990–2017. We construct the spillover index for the Chinese financial cycle to investigate the general and time-varying features. Then Chinese financial cycle net spillovers are considered to fit a Markov-switching autoregressive model.

Our main findings can be summarized as follows. First, Chinese financial cycle spillovers have several general characteristics, with a significant difference in the directional spillovers to other countries. The financial cycle spillover from China is the largest to France and the smallest to the United Kingdom, 11.20 and 2.89, respectively. And the Chinese financial cycle directional spillovers exceed the average developed countries' spillover. In addition, the Chinese financial cycle directional spillovers are relatively unbalanced than in most developed countries.

Second, Chinese financial cycle net spillovers have significant time-varying features, which are very sensitive to specific events. The Chinese financial cycle net spillover index value is normally around 5–15%; however, during certain periods, the spillover increases to as much as 56.0 or decreases to as little as –11.8. We can be roughly divided into four cycle in the net spillovers index, combined with its fluctuation and special events. Specifically, the first cycle began in 1995Q1 and ended in 1999Q4, during which Chinese financial cycle net spillover index shows its instability. The second cycle started in 2000Q1 and ended in 2007Q3, during which Chinese financial cycle net spillovers gradually increased. The third cycle started in 2007Q4 and ended in 2013Q3, during which Chinese financial cycle net spillovers went through a trough. The fourth cycle started in 2013Q4 and ended in 2017Q4, during which Chinese financial cycle net spillovers emerged from the financial crisis. The intensification of China's financial market turmoil may have a negative impact on the already weak global economic recovery. The sharp increase in China's financial market turmoil may translate into lower global stock prices, long-term interest rates and oil prices.

Third, Chinese financial cycle net spillovers can be divided into three different regimes characterized by contraction, moderation, and expansion. Summarizing the parameter estimation of MS-AR model, we conclude that the effect of lag order on the China's financial cycle net spillover has nonlinear features. Chinese financial cycle net spillovers have a high probability of remaining in the same regime. However, the smoothed probabilities between different regimes are subject to macroeconomic regulation and control. Our empirical research also indicates that the moderation regime dominates, with asymmetry in the spillover on the likelihood of transition and smoothed likelihood between different regimes.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Adam K, Marcet A, Nicolini JP (2016) Stock market volatility and learning. *J Financ* 71: 419–438.

Ahi K, Laidroo L (2019) Banking market competition in Europe—financial stability or fragility enhancing? *Quant Financ Econ* 3: 257–285.

Aikman D, Haldane AG, Nelson BD (2015) Curbing the credit cycle. *Econ J* 125: 1072–1109.

Alessi L, Detken C (2011) Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *Eur J Polit Econ* 27: 520–533.

Aloui R, Aïssa MSB, Nguyen DK (2011) Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *J Bank Financ* 35: 130–141.

Antonakakis N, Badinger H (2014) International business cycle spillovers since the 1870s. *Appl Econ* 46: 3682–3694.

Antonakakis N, Breitenlechner M, Scharler J (2015) Business cycle and financial cycle spillovers in the G7 countries. *Q Rev Econ Financ* 58: 154–162.

Antonakakis N, Vergos K (2013) Sovereign bond yield spillovers in the Euro zone during the financial and debt crisis. *J Int FinancMark Inst Money* 26: 258–272.

Back J, Prokopczuk M, Rudolf M (2013) Seasonality and the valuation of commodity options. *J Bank Financ* 37: 273–290.

Bahmani-Oskooee M, Saha S (2019) On the effects of policy uncertainty on stock prices: an asymmetric analysis. *Quant Financ Econ* 3: 412–424.

Bekaert G, Ehrmann M, Fratzscher M, et al. (2014) The global crisis and equity market contagion. *J Financ* 69: 2597–2649.

Bernanke BS, Gertler M, Gilchrist S (1999) The financial accelerator in a quantitative business cycle framework, *Handbook of Macroeconomics,* vol. 1, TaylorJ. B., WoodfordM., eds. Elsevier, 1341–1393.

Bessler W, Wolff D (2015) Do commodities add value in multi-asset portfolios? An out-of-sample analysis for different investment strategies. *J Bank Financ* 60: 1–20.

Borio C (2014) The financial cycle and macroeconomics: What have we learnt? *J Bank Financ* 45: 182–198.

Borio C, Kennedy N, Prowse SD (1994) Exploring aggregate asset price fluctuations across countries: measurement, determinants and monetary policy implications. BIS Economics Paper.

Borisova G, Megginson WL (2011) Does government ownership affect the cost of debt? Evidence from privatization. *Rev Financ Stud* 24: 2693–2737.

Böninghausen B, Zabel M (2015) Credit ratings and cross-border bond market spillovers. *J Int Money Financ* 53: 115–136.

Broni MY, Masih M (2019) Does a country's external debt level affect its Islamic banking sector development? evidence from Malaysia based on quantile regression and markov regime switching. *Quant Financ Econ* 3: 366–389.

Chiang SM, Chen HF, Lin CT (2013) The spillover effects of the sub-prime mortgage crisis and optimum asset allocation in the BRICV stock markets. *Global Financ J* 24: 30–43.

Christiansen C (2007) Volatility-spillover effects in European bond markets. *Eur Financ Manage* 13: 923–948.

Claessens S, Kose MA, Terrones ME (2012) How do business and financial cycles interact? *J Int Econ* 87: 178–190.

Comunale M, Hessel J (2014) Current account imbalances in the Euro area: Competitiveness or financial cycle? De Nederlandsche Bank Working Paper No. 443.

Degiannakis S, Duffy D, Filis G, et al. (2016) Business cycle synchronisation in EMU: Can fiscal policy bring member-countries closer? *Econ Model* 52: 551–563.

Del Negro M, Otrok C (2008) Dynamic factor models with time varying parameters: Measuring changes in international business cycles. Federal Reserve Bank of New York Staff Reports 326.

Detken C, Smets F (2004) Asset price booms and monetary policy. *Social Sci Electronic Publ* 42: 189–232.

Diebold FX, Yilmaz K (2009) Measuring financial asset return and volatility spillovers, with application to global equity markets. *Econ J* 119: 158–171.

Diebold FX, Yilmaz K (2012) Better to give than to receive: Predictive directional measurement of volatility spillovers. *Int J Forecasting* 28: 57–66.

Drehmann M, Borio C, Tsatsaronis K (2012) Characterising the financial cycle: Don't lose sight of the medium term! BIS papers 380, Bank for International Settlements.

Eickmeier S, Gambacorta L, Hofmann B (2014) Understanding global liquidity. *Eur Econ Rev* 68: 1–18.

Engle DM, Stritzke JF, Bidwell TG, et al. (1993) Late-summer fire and follow-up herbicide treatments in tallgrass prairie. *J Range Manage*, 542–547.

Fidrmuc J, Korhonen I (2006) Meta-analysis of the business cycle correlation between the Euro area and the CEECs. *J Comp Econ* 34: 518–537.

Filardo A, George J, Loretan M, et al. (2010) The international financial crisis: Timeline, impact and policy responses in Asia and the Pacific. *BIS Pap* 52: 21–82.

Francq C, Zakoıan JM (2001) Stationarity of multivariate Markov–switching ARMA models. *J Econ* 102: 339–364.

Geweke JF (1977) *The Dynamic Factor Analysis of Economic Time Series Models.* Aigner D.J., Goldberger A.S. (Eds.), Latent Variables in Socio-Economic Models, North Holland, Amsterdam, 365–383.

Goodhart C, Hofmann B (2001) Asset prices, financial conditions, and the transmission of monetary policy. In *conference on Asset Prices, Exchange Rates, and Monetary Policy, Stanford University*, 2–3.

Goodhart C, Hofmann B (2008) House prices, money, credit, and the macroeconomy. *Oxford Rev Econ Policy* 24: 180–205.

Gupta R, Wohar ME (2018) The role of monetary policy uncertainty in predicting equity market volatility of the United Kingdom: Evidence from over 150 years of data. Working Papers 201851, University of Pretoria, Department of Economics.

Hasmath R, Hsu J (2007) Big business, NGOs and labour standards in developing nations: a critical reflection. *Asian J Soc Policy* 3: 1–15.

IMF (2016) Global Financial Stability Report: Potent Policies for a Successful Normalization.

Jammazi R (2014) Oil shock transmission to stock market returns: Wavelet-multivariate Markov switching GARCH approach. *Energy* 37: 430–454.

Ji Q, Liu BY, Cunado J, et al. (2018) Risk spillover between the US and the remaining G7 stock markets using time-varying copulas with Markov switching: Evidence from over a century of data. *North Am J Econ Financ*. Advance online publication.

Jordà Ò, Schularick M, Taylor AM, et al. (2017) Global Financial Cycles and Risk Premiums. IMF Working Paper, International Monetary Fund, Washington, DC.

Kaminska I, Roberts-Sklar M (2018) Volatility in equity markets and monetary policy rate uncertainty. *J Empir Financ* 45: 68–83.

Ke J, Wang LM, Murray L (2010) An empirical analysis of the volatility spillover effect between primary stock markets abroad and China. *J Chinese Econ Bus Stud* 8: 315–333.

Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. *J Economet* 74: 119–147.

Li L, Yin L, Zhou Y (2016) Exogenous shocks and the spillover effects between uncertainty and oil price. *Energy Econ* 54: 224–234.

Li T, Zhong J, Huang Z (2019) Potential Dependence of Financial Cycles between Emerging and Developed Countries: Based on ARIMA-GARCH Copula Model. *Emerg Mark Financ Trade*, Advance online publication.

Li ZH, Dong H, Huang ZH, et al. (2018) Asymmetric effects on risks of virtual financial assets (VFAs) in different regimes: A case of Bitcoin. *Quant Financ Econ* 2: 860–883.

Li Z, Zhong J (2019) Impact of economic policy uncertainty shocks on China's financial conditions. *Financ Res Lett,* Advance online publication.

Liu Q, Tse Y, Zhang L (2018) Including commodity futures in asset allocation in China. *Quant Financ* 18: 1487–1499.

Londono JM, Zhou H (2017) Variance risk premiums and the forward premium puzzle. *J Financ Econ* 124: 415–440.

Mankiw NG, Reis R (2002) Sticky information versus sticky prices: A proposal to replace the new Keynesian Phillips curve. *Q J Econ* 117: 1295–1328.

Menden C, Proaño CR (2017) Dissecting the financial cycle with dynamic factor models. *Quant Financ* 17: 1965–1994.

Mensi W, Hammoudeh S, Nguyen DK, et al. (2016) Global financial crisis and spillover effects among the US and BRICS stock markets. *Int Rev Econ Financ* 42: 257–276.

Miranda-Agrippino S, Rey H (2015). World asset markets and the global financial cycle. NBER Working Paper.

Ng T (2011) The predictive content of financial cycle measures for output fluctuations. BIS Quarterly Review, Bank for International Settlements.

Papadimitriou T, Gogas P, Sarantitis GA (2014) European Business Cycle Synchronization: A Complex Network Perspective, In *Network Models in Economics and Finance*, Springer, Cham, 265–275.

Pesaran HH, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. *Econ Lett* 58: 17–29.

Qamruzzaman M, Wei J (2019) Do financial inclusion, stock market development attract foreign capital flows in developing economy: a panel data investigation. *Quant Financ Econ* 3: 88–108.

Rapach DE, Strauss JK, Wohar ME (2008) Chapter 10 Forecasting Stock Return Volatility in the Presence of Structural Breaks. D.E. Rapach, M.E. Wohar (Eds.), *Forecasting in the Presence of Structural Breaks and Model Uncertainty*, Vol. 3 of Frontiers, Emerald Series Frontiers of Economics and Globalization, Emerald, Bingley, UK, 381–416.

Reboredo JC, Rivera-Castro MA, Ugolini A (2016) Downside and upside risk spillovers between exchange rates and stock prices. *J Bank Financ* 62: 76–96.

Roni B, Abbas G, Wang S (2018) Return and Volatility Spillovers Effects: Study of Asian Emerging Stock Markets. *J Syst Sci Inf* 6: 97–119.

Sargent TJ, Sims CA (1977) Business cycle modeling without pretending to have too much a priori economic theory. *New Methods Bus Cycle Res* 1: 145–168.

Savva CS, Neanidis KC, Osborn DR (2010) Business cycle synchronization of the Euro area with the new and negotiating member countries. *Int J Financ Econ* 15: 288–306.

Schularick M, Taylor AM (2009) Credit booms gone bust: Monetary policy, leverage cycles and financial crises, 1870–2008. *Am Econ Rev* 102: 1029–1061.

Schüler YS, Hiebert PP, Peltonen TA (2015) Characterising the financial cycle: A multivariate and time-varying approach. ECB Working Paper Series 1846, European Central Bank.

Singh P, Kumar B, Pandey A (2010) Price and volatility spillovers across North American, European and Asian stock markets. *Int Rev Financ Anal* 19: 55–64.

Stock JH, Watson MW (1989) New indexes of coincident and leading economic indicators. *NBER Macroecon Annu* 4: 351–394.

Wang GJ, Xie C, He K, et al. (2018) Extreme risk spillover network: application to financial institutions. *Quant Financ* 17: 1–23.

Wang Y, Pan Z, Wu C (2018) Volatility spillover from the US to international stock markets: A heterogeneous volatility spillover GARCH model. *J Forecasting* 37: 385–400.

Wei KCJ, Liu YJ, Yang CC, et al. (1995) Volatility and price change spillover effects across the developed and emerging markets. *Pac-Basin Financ J* 3: 113–136.

Wu F, Guan Z, Myers RJ (2011) Volatility spillover effects and cross hedging in corn and crude oil futures. *J Futures Mark* 31: 1052–1075.

Zhong J, Wang M, Drakeford B, et al. (2019) Spillover effects between oil and natural gas prices: Evidence from emerging and developed markets. *Green Financ* 1: 30–45. Doi: 10.3934/GF.2019.1.30.