Research article

Chinese financial cycle spillovers to developed countries

Tinghui Li[1], Junhao Zhong[1],*, Hai Zhang[2] and Pierre Failler[3]

[1] School of Economics and Statistics, Guangzhou University, Guangzhou 510006, China
[2] Department of Accounting & Finance, Strathclyde Business School, Glasgow G4 0QU, UK
[3] Department of Economics and Finance, Portsmouth Business School, University of Portsmouth, Portsmouth, P01 3DE, UK

* Correspondence: Email: 2111764009@e.gzhu.edu.cn; Tel: +8618576316991.

Abstract: In this paper, we quantify the spillovers of Chinese financial cycles from 1990Q1 to 2017Q4. We construct a spillover index for Chinese financial cycles and fit the Markov-switching autoregressive model. Our main findings indicate that Chinese financial cycle spillover shows several general characteristics and has significant time-varying features that are very sensitive to specific events. We examine the three different regimes of net spillovers, labeling them contraction, moderation, and expansion, and find that the moderation regime dominates.

1. Introduction

Recently, many studies investigating cyclical volatility focus on spillover effects. Spillover of the financial cycle has critical implications for option pricing, asset allocation, and risk management (Rapach, Strauss, & Wohar, 2008; Adam, Marcet, & Nicolini, 2016; Londono & Zhou, 2017; Wang, Pan, & Wu, 2018). The spillover effect creates an external shock to asset prices (Jammazi, 2014; Li et al., 2016; Li & Zhong, 2019) and a disturbance in the assessment and management of asset allocation (Bessler & Wolff, 2015; Liu et al., 2018). In addition, many papers find that the spillover effect of financial cycles reveals the channel of financial risk contagion (Bekaert et al., 2014; Wang et al., 2018). In the context of deepening financial development and accelerating international capital

flows, it is necessary to expand the scope of research on the financial cycle. Investigating the spillover effects of financial cycle volatility is not only a useful supplement to existing research, but also important for preventing international financial risk transmission and promoting regional financial stability. Hence, we build on the previous research to further reveal the spread of such spillovers across different financial cycles in different periods.

The notion of the financial cycle is mentioned in many papers in macroeconomics. In some mainstream literature, the financial cycle is defined as the booms and busts in the credit, housing, and equity markets (Claessens et al., 2012; Borio, 2014; Li et al., 2019). More generally, they identify the financial cycle with a medium-term component in the fluctuations of credit and property prices (Drehmann et al., 2012). Other papers parsimoniously describe the financial cycle as credit growth (Aikman et al., 2015; Antonakakis et al., 2015). But the best way to approximate the financial cycle empirically should include the following five features: it is most parsimoniously described in terms of credit and property prices; it has a much lower frequency than the traditional business cycle; its peaks are closely associated with financial crises; it helps detect financial distress risks with a good lead in real time; its length and amplitude depend on policy regimes (Borio, 2014).

To date, financial cycle spillovers from China to developed countries have received little attention. The financial cycle spillover effect in this article actually measures the total amount of volatility shocks between international financial markets. Most of the literature focuses on spillovers between the United States and Europe (Christiansen, 2007; Diebold & Yilmaz, 2012; Antonakakis & Vergos, 2013; Gupta & Wohar, 2018) or from developed countries to emerging countries (Wei et al., 1995; Aloui, Aïssa, & Nguyen, 2011; Mensi et al., 2016). Because of their particular characteristics and their increasingly important role in the global economy in terms of both market share and economic growth, emerging markets merit research attention. In particular, external spillover effect from China has increased since the liberalization of its financial markets.

Several factors that trigger financial cycle spillovers from China to other economies can be summarized as follows. First, China has a large trade surplus. According to the CIA World Factbook, as of December 2017, China's net exports totaled to $495 billion. Second, the renminbi (RMB) has become internationalized since the International Monetary Fund (IMF) voted to include it as a world currency, in the basket of special drawing rights (SDR) in November 2015. Third, China's investment and aid to foreign countries have reached a record high. As of the end of 2017, China's foreign direct investment (FDI) was $1.8 trillion, ranking second in the world.

Spillover effects from emerging countries are becoming more diversified and related to more market linkage (Chiang et al., 2013; Mensi et al., 2016; Roni et al., 2018). In addition, their periodicity and asymmetry are increasing. Before the 2008 global financial crisis, a bidirectional volatility spillover effect was seen between two markets, whereas after the crisis a unidirectional volatility spillover effects come from the Chinese financial market to other financial markets (Ke et al., 2010; Zhong et al., 2019), and these spillover effects are measurable. For example, the spillover effect of China's industrial sector on share prices in the basic metals sector of developed economies has increased, from 1.5% in the past to 5% after the global financial crisis (IMF, 2016).

Financial cycle spillovers are important because they are prerequisites for the smooth and efficient operation of monetary policy. The spillover of the financial cycle will have an asymmetric shock that will hit each economy and will inevitably lead to the implementation of monetary policy unless financial cycles are synchronized (Fidrmuc & Korhonen, 2006; Savva et al., 2010; Papadimitriou et al., 2014; Degiannakis et al., 2016; Qamruzzaman and Wei, 2019). The spillovers

are transmitted across both fixed and floating exchange rate regimes, indirectly affecting monetary policy (Miranda-Agrippino & Rey, 2015; IMF, 2017). Some evidence suggests that the uncertainty of monetary policy in those country is also appearing to trigger financial cycle volatility (Gupta & Wohar, 2018; Kaminska & Roberts-Sklar, 2018).

Financial cycle spillovers may be affected by several main channels, which can be broadly divided into external and internal influence. External influence can be regarded as the effect of political factors on volatility spillovers, and internal influence can be regarded as the effect of financial market factors. In terms of external influence, the effect of political factors on volatility spillovers can be summarized as follows. Governments try to exert political influence on financial market volatility and guide volatility spillovers (Borisova & Megginson, 2011; Antonakakis & Vergos, 2013; Bahmani-Oskooee and Saha, 2019). A country's central bank tries to stabilize the currency as much as possible and avoid a serious expansion of debt leverage to prevent excessive shocks caused by periodic resurgence. In terms of internal influence, the effect of financial market factors on volatility spillovers can be summarized as the cyclical adjustment of financial asset prices and asset size in financial markets is seasonal, which leads to the strengthening or weakening of financial cycle spillovers (Singh et al., 2010; Wu et al., 2011; Back et al., 2013; Ahi and Laidroo, 2019).

We make three contributions to the literature. First, we investigate spillovers focusing on the financial cycle. To date, most of the literature focuses on two research topics. The first is spillover effects on the business cycle (Diebold & Yilmaz, 2009; Antonakakis & Badinger, 2014), and the second is asset prices, such as stocks, bonds, and exchange rates (Böninghausen & Zabel, 2015; Reboredo et al., 2016). Second, we highlight and empirically analyze unidirectional spillovers of the financial cycle from China to developed countries. Predecessors have done a lot of work on spillover effects from developed countries to emerging countries. Finally, in identifying the Chinese financial cycle spillover regimes, we illustrate the nonlinear and asymmetrical features of a spillover index.

The remainder of the paper is organized as follows. In Section 2, we present our basic theory, beginning with a definition of the financial cycle and analyze China's financial cycle spillovers. In Section 3, we measure the financial cycle and discuss our methodology. In Section 4, we calculate the spillover index of Chinese financial cycle. In Section 5 we analyze the nonlinear and asymmetrical features of Chinese financial cycle spillovers in different regimes. Finally, the last section concludes and gives suggestions for future research.

2. Theoretical analysis

2.1. Definition of the financial cycle

The definition of the financial cycle has evolved over time. Initially, many scholars, such as David Ricardo and Joseph Schumpeter, focused on the currency and credit cycle, regarding it as the preliminary stage of the financial cycle. Not until the premise of financially neutral theory was modified did financial cycle theory achieve a breakthrough. Before the financial crisis, some scholars proposed the theory of a financial economic cycle or a general business cycle (e.g., Bernanke at el., 1999; Mankiw & Reis, 2002). After the outbreak of the financial crisis in 2008, research on the effect of financial cyclical fluctuations on macroeconomics advanced and became more in-depth (Claessens et al., 2012; Ng, 2011; Drehmann et al., 2012; Borio, 2014; Aikman et al., 2015). The

literature has proliferated and now considers a large number of financial market factors as well as exploring the root cause of periodic fluctuations.

Before we define the financial cycle, we explain the links and differences between the financial cycle and the business cycle, as seen in Table 1. The business cycle generally refers to the regular expansion and contraction experienced by economic activities in the course of economic development. The business cycle emphasizes cyclical fluctuations in the expansion and contraction of the gross domestic product (GDP), total income, and total employment. The link between the financial cycle and the business cycle is in reflecting cyclical fluctuations in the macroeconomy, and the financial cycle has a predictive effect on the business cycle.

Table 1. The differences between the financial cycle and the business cycle.

	Financial cycle	Business cycle
Definition	No general consensus has been reached on the definition of the financial cycle. It mainly refers to the cyclical fluctuations caused by the expansion and contraction of credit and financial asset prices, such as equity, credit, and housing prices.	The business cycle, also known as the economic cycle or trade cycle, is the downward and upward movement in the gross domestic product (GDP) around its long-term growth trend.
Measuring	No uniformity exists regarding measurement of financial cycles.	Business cycles are usually measured by considering the growth rate of real GDP.
Frequency	The frequency of the financial cycle is much lower than that of the traditional business cycle.	The frequency of the business cycle is generally 1–8 years.
Impact factor	Fluctuations in credit or debt.	For example, technological progress.

The financial cycle reflects the dynamics of credit and various financial asset prices at different stages of economic fluctuations. Despite the large number of recent studies, no general consensus has been reached on a definition of the financial cycle (Borio, 2014). Most research defines the financial cycle in two ways. First, the financial cycle focuses exclusively on credit, so the financial cycle is identified with a component in the joint fluctuations of credit and asset price (Bernanke et al., 1999; Alessi & Detken, 2011; Aikman et al., 2015). Second, financial cycles combine statistically a variety of financial price and quantity variables, to extract their common components (Goodhart & Hofmann, 2001; Ng, 2011; Eickmeier et al., 2014; Menden & Proaño, 2017). Scholars have different definitions of the financial cycle, using credit and asset prices to measure the financial cycle or constructing a comprehensive index.

Combining the experience of predecessors, we define the financial cycle as cyclical fluctuations caused by the expansion and contraction of credit and financial asset prices, such as equity, credit, and housing prices. That is, the financial cycle can be explained through dynamic trends in credit and financial asset prices at different stages of economic fluctuations. Specifically, the price of a financial asset is the value of any financial instrument owned by an organization or individual that can be traded in a financial market with real prices and future valuations. The volatility of financial assets at the price level is usually reflected in booms and busts in the financial cycle. The recent financial crises show that the source of financial instability is severe change in credit and financial asset prices affect the financial cycle through arbitrage, exchange rates, and interest rate policy (Borio et al., 1994;

Detken & Smets, 2004; Goodhart & Hoffman, 2008; Schularick & Taylor, 2009; Schüler et al., 2015). Therefore, credit and financial asset prices are the essential factors. Following the setting of Claessens et al. (2012), we finally chose these five variables, equity price, credit scale, house price, interest rate and exchange rate.

2.2. *Chinese financial cycle spillovers to other countries*

Chinese financial cycle spillovers can be measured in terms of total spillovers, directional spillovers, net spillovers. Total spillovers represent the contribution of spillovers to financial cycles between China and other countries to those in all countries' financial cycles. Directional spillovers are those received by the Chinese financial cycle from other countries' financial cycles and those transmitted by the Chinese financial cycle to those in other countries. Net spillovers represent spillovers from the Chinese financial cycle to that of other countries minus the spillovers from other countries' financial cycles to China's.

The shape of Chinese financial cycle spillovers has three determinants. First, it has increasing scale because China's FDI flows have expanded to the point of being the world's third largest, behind only the United States and Japan. This behavior directly increases China's spillover effects on other countries. In addition, China has a high degree of financial openness, with a sophisticated stock market, which generates more financial links between the Chinese market and those in other countries. Finally, Chinese financial cycle spillovers are affected by Chinese government policies. For example, fluctuation in the RMB exchange rate and monetary policy can lead to unidirectional spillovers from Chinese financial cycle volatility.

The Chinese financial cycle spillovers demonstrate three different regimes[1]: expansion, moderation, and contraction. These regimes can be difficult to determine because of nonlinear and asymmetrical features. The risks in Chinese financial markets in different periods affect the fluctuations in Chinese financial cycle spillovers with the degree of financial openness and macro-control policies. Based on this, we use a Markov-switching autoregressive model to analyze the nonlinear and asymmetry feature of Chinese financial cycle spillovers.

3. Methodology

3.1. *Measuring financial cycles*

Financial cycles are usually measuring using a dynamic factor model (DFM). Geweke (1977) and Sargent and Sims (1977) first proposed the DFM in economics, which is the extension of the classical factor model in time-series data. Stock and Watson (1989) assume that a panel dataset can be characterized by one or more latent common components that capture the comovements of the cross section. DFM analyzes the financial cycle based on factor analysis theory, examining the dynamic relationship in those cycles by extracting the volatility information in high-dimensional financial variables.

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[1] After many attempts, we singled out the three-regime Markov switching model to obtain the dynamic characteristics of Chinese financial cycle spillover effects based on the minimum AIC value criterion and the significant p-value of the regression coefficient.

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

$$FC_t = \Lambda_t f_t + U_t,$$ (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:

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

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

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

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

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

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

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

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

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

$$\sum_{j=1}^{N}\theta_{ij}\left(H\right)\neq1.$$

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:

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

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

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

$$TS\left(H\right)=\frac{\sum_{\substack{i,j=1\\i\neq j}}^{N}\tilde{\theta}_{ij}\left(H\right)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}\left(H\right)}\times100=\frac{\sum_{\substack{i,j=1\\i\neq j}}^{N}\tilde{\theta}_{ij}\left(H\right)}{N}\times100 \tag{9}$$

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

$$DS_{i\rightarrow}\left(H\right)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}\left(H\right)}{\sum_{j=1}^{N}\tilde{\theta}_{ji}\left(H\right)}\times100 \quad \text{and} \quad DS_{i\leftarrow}\left(H\right)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}\left(H\right)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}\left(H\right)}\times100 \tag{10}$$

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

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

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 $\varepsilon_t \sim N(0, \sigma^2)$ 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 $s_t^* = (s_t, s_{t-1}, \cdots, s_{t-p})$, 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 $j = (j_0, j_1, \cdots, j_p)$, with $j_i \in \{0, 1, \cdots, K-1\}$, $i = 0, 1, \cdots, p$. Then, the transition probabilities of s_t^* are

$$P\left(s_t^* = \mathrm{j} \mid s_{t-1}^* = \mathrm{i}\right) := p_{\mathrm{ij}}^*$$

$$= \begin{cases} p_{i_0 j_0} & \text{always } i_r = j_{r-1} \text{ for } r = 1, 2, ..., p \\ 0 & \text{otherwise.} \end{cases} \qquad (14)$$

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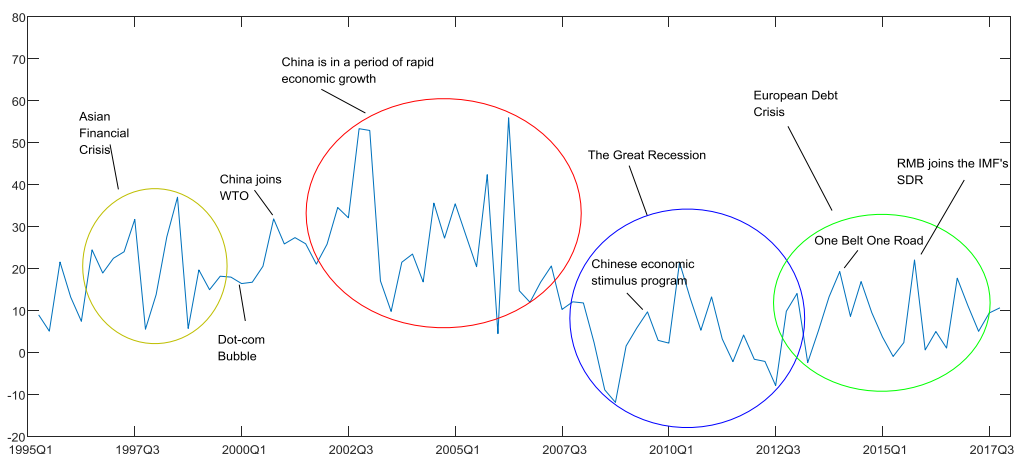
Figure 1. Financial cycle net spillovers from China to developed countries. Note: VAR lag used in the estimation is 2, step of forecasting horizon is 4 quarters, and rolling-window length is 20 quarters.

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

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[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.
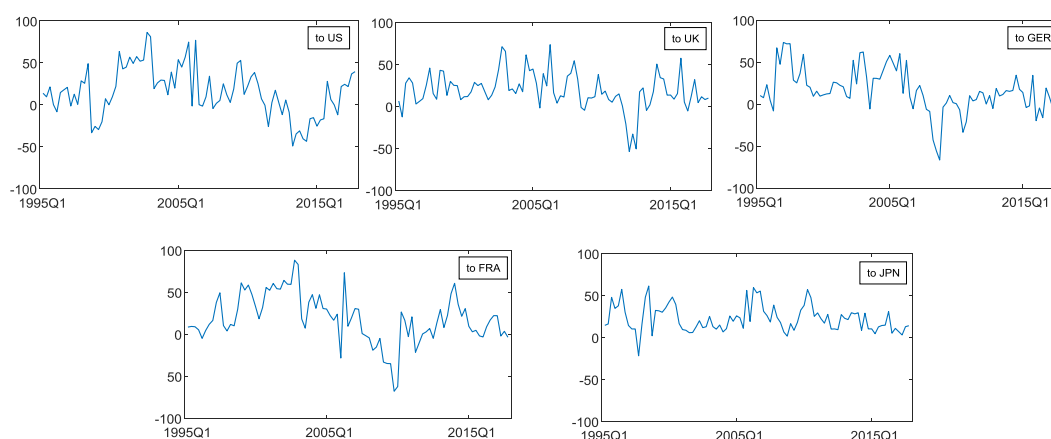

Figure 2. Financial cycle net spillovers from China to developed countries. Note: VAR lag used in the estimation is 2, step of forecasting horizon is 4 quarters, and rolling-window length is 20 quarters.

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.

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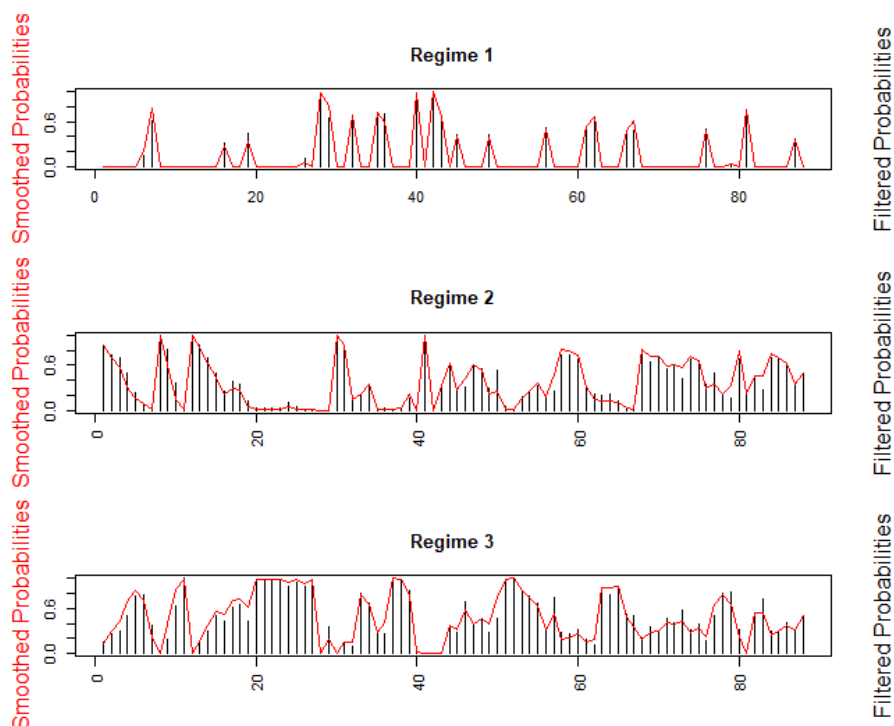
Figure 3. Smoothed and filtered probabilities of net spillovers of Chinese financial cycles.

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.

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