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Contact to corresponding author: Marinko Skare, mskare@unipu.hr

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Shengnan Lv
Sichuan University, China
orcid.org/0000-0002-7697-7550

Zeshui Xu
Sichuan University, China
orcid.org/0000-0003-3547-2908

Xuecheng Fan
Sichuan University, China
orcid.org/0000-0001-9478-3795

Yong Qin
Sichuan University, China
orcid.org/0000-0002-4966-7899

Marinko Skare
Juraj Dobrila University Pula, Croatia
University of Economics and Human Sciences in Warsaw, Poland
orcid.org/0000-0001-6426-3692

The mean reversion/persistence of financial cycles: Empirical evidence for 24 countries worldwide

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Abstract

Research background: The globalization trend has inevitably enhanced the connectivity of global financial markets, making the cyclicality of financial activities and the spread of market imbalances have received widespread attention, especially after the global financial crisis.
Purpose of the article: To reduce the negative effects of the contagiousness of the financial cycles, it is necessary to study the persistence of financial cycles and carve out the total connectedness, spillover paths, and sources of risks on a global scale. In addition, understanding the relationship between the financial cycle and economic development is an important way to prevent financial crises.
Methods: This paper adopts the nonlinear smoothing transition autoregressive (STAR) model to extract cyclical and phase characteristics of financial cycles based on 24 countries during 1971Q1–2015Q4, covering developed and developing countries, the Americas, Europe, and Asia regions. In addition, the frequency connectedness approach is used to measure the connectedness of financial cycles and the relationship between the global financial cycle and the global economy.
Findings & value added: The analysis reveals that aggregate financial cycles persist for 13.3 years for smoothed and 8.7 years for unsmoothed on average. The national financial cycles are asynchronous and exhibit more prolonged expansions and faster contractions. The connectedness of financial cycles is highly correlated with systemic crises and contributes to the persistence and harmfulness of shocks. It is mainly driven by short-term components and exhibits more pronounced interconnectedness within regions than across regions. During the financial crisis, the global financial cycle movements precede and are longer than the business fluctuations. Based on the study, some policy implications are presented. This paper emphasizes the impact of systemic crises on the persistence of financial cycles and their connectedness, which contributes to refining research related to the coping mechanisms of financial crises.

Introduction

Global financial integration and deepening macro-financial linkages have exacerbated rapid cross-border spillovers of systemic financial risks. Specifically, a shock in a segment-specific financial market can quickly spread to other areas and devastatingly impact the national or even the global economy (see Adarov, 2021). For example, the shock of the bursting regarding the USA mortgage crisis in 2007 caused a national banking collapse that quickly spread from the USA to the rest of the world. Another example is the four crashes in the USA stocks on March 9, 12, 16, and 23, 2020, caused by government's reaction to COVID-19 (see Mazur *et al.*, 2021). These crushes triggered a spate of stock market declines in major Western countries and global economic setbacks. The events of systemic financial crises drew the attention of governments and made us curious about the nature of financial cycles, their impacts, and how they contaminate globally (see Skare & Porada-Rochon, 2020; Maciejewski & Głodowska, 2020).

The financial cycle has been one of the hot topics since the global financial crisis. Its volatility is often associated with fluctuations in credit, housing, bond, and equity markets (see Li *et al.*, 2021; de Winter *et al.*, 2022). On this basis, a large number of studies have obtained the durations and amplitudes of national/global financial cycles based on data from single or multiple financial submarkets as mentioned above. However, relevant literature has not yet reached uniform conclusions due to differences in samples and methodologies. Most of the studies show an average duration of 9–15 years for financial cycles, and that the length and magnitude of financial cycles are more persistent than traditional business cycles (see Borio, 2014; Yan & Huang, 2020; Adarov, 2022). The business cycle tends to be measured by the aggregate economic activity of business enterprises, while financial cycle is often estimated by the activity of financial markets (see Trotta Vianna, 2023).

Moreover, numerous studies have shown that financial and geopolitical events in a country are devastating to the economy, in particular, systemic financial crises may lead to cross-border comovements of national financial cycles (see Pineda *et al.*, 2022). For this reason, a large number of static and dynamic analyses of financial cycle contagion have been presented to analyze dynamic correlations and cross-country spillover effects. These studies show that financial crises and COVID-19 pandemic promote financial cycle connectedness across countries and that the resulting risks and shocks occur mainly in the short run (see Barunik & Křehlík, 2018; Akhtaruzzaman *et al*., 2021). In addition, shocks originating in developed economies have a strong impact on other economies, and the higher the degree of interdependence among countries the more contagious the financial cycle will be (see Fałdziński *et al*., 2016; Polat, 2022).

Despite the current basic understanding of the financial cycle, there is still a need for a systematic analysis of the financial cycle itself and its spillover characteristics given its significant impact on the economy. In order to develop a systematic, comprehensive, and accurate portrayal of the characteristics and connectedness of financial cycles, this paper studies the mean reversion/persistence performances of financial cycles and their connectedness based on 24 countries around the world from 1971Q1 to 2015Q4, including developed and developing countries, the Americas, Europe, and Asia regions. We measure the nature and characteristics of financial cycles by using the smoothing transition autoregressive (STAR) model, which can describe the nonlinear transformation characteristics from contraction to expansion phase through a transition function consistent with the actual financial operation. In doing so, the spectral representation of the generalized forecast error variance decompositions (GFEVD) method (also known as the frequency connectedness approach) is used to measure the connectedness of financial cycles on a global scale. This approach can help us estimate the connectedness of financial cycles in short- and long-term frequency bands and disentangle the shock sources of connectedness among financial variables. Finally, the relationship between the global financial cycle and the global economy is discussed.

Compared with the existing research, the possible contributions of this study are as follows: (1) In terms of scope, this paper uses broader sample data and a more representative financial cycle index, making the related conclusions of financial cycles and financial connectedness more general understanding than evidence from a specific financial market or region. (2) As for methodology, unlike other studies, our work adopts the nonlinear STAR model to extract cyclical and phase characteristics of financial cycles. (3) With respect to scientific highlights, this paper emphasizes the impact of systemic crises on the cyclical nature of financial cycles and their connectedness, which contributes to refining research related to the coping mechanisms of financial crises.

The paper is organized as follows: Section 2 provides reviews of the related literature. Section 3 reports the data on the study and describes the methodology. Section 4 measures and discusses the duration and interconnectedness networks of financial cycles through the STAR model and frequency connectedness approach. Section 5 provides some discussions and implications. In Section 6, conclusions are drawn.

Literature review

Currently, there is no unified definition of the financial cycle. Borio (2014) described the financial cycles as self-reinforcing interactions among perceptions of value and risk, risk perception, and financing constraints. In general, financial cycles are usually characterized by a boom-to-bust transition, beginning with a financial boom driven by credit growth and ample liquidity (we call this phase the expansion phase), followed by a financial bust with declining asset prices, reduced credit activity, expansion, and increased market volatility (we call this phase is the contraction phase) (see Borio, 2014; Jing *et al*., 2022).

Specifically, financial cycles depend on the existing financial, monetary and real economic policy regimes and are closely related to systemic banking crises, in particular, financial market activity associated with risk perception and liquidity constraints can trigger major financial crises (see Borio *et al*., 2017; Dutra *et al*., 2022). According to research by Brandão-Marques *et al*. (2022), the riskiness of credit allocation helps predict shifts in the left tail of the GDP growth distribution and financial stress episodes. Adrian *et al*. (2022) argued that financial conditions significantly affect growth-at-risk and that loose financial conditions have a causal relationship with future downside risk. More noteworthy is that the financial cycles are an essential reference for predicting the risk of economic recession and a prerequisite for dealing with economic fluctuations (see Borio *et al*., 2019; Li *et al*., 2021).

On this basis, an increasing number of empirical studies have focused on the estimation and analysis of financial cycles. For example, Skare and Porada-Rochon (2020) used the data of total credit, credit-to-GDP ratios, and long-run property prices to research financial cycles for ten developed economies over 1970–2018 by the multi-channel singular spectrum, showing that the global financial cycle lasts 9–11 years, on average. More comprehensively, Adarov (2022) studied the aggregate financial cycles of 34 countries based on credit, housing, bond, and equity markets by using an individual state-space model, based on which the average period was measured to be 9-15 years. The persistence of financial cycles can be shorter in developing countries. Gammadigbe (2022) examined the duration and amplitude of the financial cycle of the West African Economic and Monetary Union (WAEMU), and found that the longest average national financial cycle duration was about 7 years and the shortest about 2 years.

As a natural extension, the cross-country spillover effects of financial cycles and the characteristics of global financial cycles have received much attention. Among them, Gong and Kim (2018) studied the synchronization of financial cycles in East Asia, Latin America, and Central and Eastern Europe, finding that regional business cycle synchronization benefits from regional trade integration while suffering from regional finance integration. This study exposes the static mutual contagions of financial cycles in selected countries over a given period.

Moreover, considering the hidden, complex, and time-varying characteristics of financial cycles and their contagion effects, Diebold and Yilmaz (2012, 2014) applied (GFEVD) to measure financial connectedness during the global financial crisis. After that, Barunik and Křehlík (2018) combined GFEVD with spectral representation to estimate connectedness and decompose connectedness into short-, medium-, and long-term. Akhtaruzzaman *et al*. (2021) studied the sensitivity of the volatility spillover between China and G7 financial and non-financial enterprises before and after the first confirmed case of COVID-19. The results showed increased conditional correlations between stock returns across countries and higher hedging costs during the COVID-19 pandemic. Using an extension of the DCC-GARCH model, Pineda *et al*. (2022) investigated financial contagion among the United States, China, and five European countries, revealing the contagion effects in financial markets during the subprime, European, and COVID-19 crises. The above research reveals the dynamic cross-country contagion of the financial cycles and decomposes this connectedness into different frequencies.

Although some progress has been made in understanding the cyclical characteristics and contagiousness of asset prices and financial market activity fluctuations, the majority of studies have only examined a single aspect of the persistent or static connectedness of financial cycles based on low-dimensional data from a few countries or markets. It is difficult to fully and accurately portray the prevalence of financial cycles on a global scale and the complex network of contagion. Therefore, to provide macro policymakers with more general information about financial cycles, it is necessary to study the characteristics of financial cycles on a global scale and carve out the total connectedness, spillover paths, and sources of risks of the global financial cycle.

Data and methods

Framework

The research framework of this paper is shown in Figure 1. The stages of the empirical study are as follows: Firstly, the paper estimates the average persistence of national financial cycles from 1971Q1 to 2015Q4 through the STAR model and calculates the persistence and amplitude of different phases in each country to observe the characteristics and differences of national financial cycles. After that, the total connectedness, interconnectedness and frequency decomposition of financial cycles from 1991Q1 to 2014Q4 are obtained by employing the frequency connectedness approach. The relationship between the global financial cycle and the economic development is discussed at the end.

Data

For a general discussion of financial cycles, the aggregate financial cycle index for 24 developed and developing countries around the world during 1971Q1–2015Q4 is selected to analyze the cyclical nature and amplitude of financial cycles. Region codes and country ISO3 codes are indicated in Table 1. The sample does not include African, South America and Middle Eastern countries due to the small amount of data related to financial markets in less developed countries.

The data used in this paper for financial cycles measurement are the smoothed and unsmoothed aggregate financial cycle index, which is derived from Adarov (2022). This data are extracted from a range of variables reflecting the key market characteristics (including price, quantity and risk dynamics in credit, housing, bond and equity markets) using dynamic factor models and state-space techniques. These data contain enough samples to support our study, covering major developed and developing countries as well as systemic economies, and are larger than most studies.

The summary statistics of the quarterly aggregate financial cycle index are in Table 2. Obviously, all sample means converge to 0, which implies that there may be mean reversion characteristics of financial cycles. The length of the data varies across countries. It does not affect our analysis of the lengths of national financial cycles, but it has implications for studying the mutual contagions of financial cycles. To ensure the maximum consistency in time latitude and overall integrity, we select the unsmoothed 1991Q1–2014Q4 aggregate financial cycle index for the connectedness analysis, but this does not affect the applicability of our findings. For samples with no more than two years of missing data, we use the missForest method (see Stekhoven & Buehlmann, 2012) to fill in the missing data for no more than two years.

The data collected to measure economic development include CBOE (Chicago Board Options Exchange) volatility index (VIX), the Treasury and

EuroDollar spread (TED spread) and the Aruoba-Diebold-Scotti business conditions index (ADS) from 1998Q2 to 2014Q4, which are derived from the Federal Reserve Bank of Philadelphia and Federal Reserve Economic Data. All data used in this article are quarterly.

Before conducting the research, we need to perform the Augmented Dickey-Fuller (ADF) test. Fortunately, the results confirm the stationarity of all series at least at the 10% significance level.

STAR model

At present, the theory of the linear time series model is very mature and widely used. However, more and more studies have shown that the linear model describes immutable laws, which sometimes cannot explain the constantly changing movements of financial phenomena well (see Ubilava, 2022). For example, the financial cycles usually present an asymmetric phenomenon in the expansion and contraction phases. It is difficult to accurately describe the asymmetric phenomenon with a linear model. Against this background, the research and application of nonlinear models are becoming more and more extensive.

As a nonlinear model, the STAR model can describe the nonlinear transformation characteristics from contraction to expansion phase through a transition function consistent with the actual financial operation. We use the STAR model to analyze the characteristics of the mutual transitions of various phases concerning financial cycles. The STAR model is specified as (see Terasvirta, 1994; Franses & Dijk, 2003):

$$y_t = \beta_0 + \sum_{k=1}^{K} \beta_k y_{t-k} + G(s_t, c, \gamma) \sum_{k=1}^{K} y_{t-k}\, \alpha + \varepsilon_t \tag{11}$$

where the conditional expectation y_t consists of two parts, the linear part $\beta_0 + \sum_{k=1}^{K} \beta_k y_{t-k}$, and the nonlinear part $G(s_t, c, \gamma) \sum_{k=1}^{K} y_{t-k}\, \alpha$. The two-state STAR model generalizes the standard autoregressive model to account for the varying degrees of autoregressive persistence and speed of adjustment (see Terasvirta & Anderson, 1992; Terasvirta, 1994). Besides, the argument s_t is a pre-determined transition variable. The c is a threshold parameter representing the halfway point between two phases. $G(s_t, c, \gamma)$ is the smoothing transition function with values between 0–1.

Popular transition function choices are logistic and exponential smoothing transition. The transition function selected as an exponentially smooth transition is called the exponential smoothing transition autoregressive (ESTAR) model with the following form (see Schnatz, 2007):

$$G(s_t, c, \gamma)=1 - \exp[-\gamma(s_t - c)^2] \quad (22)$$

where the $\gamma > 0$ controls the speed and smoothness of the transition function in all cases. When$\gamma \to \infty$, $G(s_t, c, \gamma)$ becomes an indicator function, the model is reduced to a threshold model. When $\gamma \to 0$, $G(s_t, c, \gamma) \to 0$, the ESTAR model is reduced to a linear model.

In the ESTAR model, the transition function is symmetric around c. As s_t approaches c, $G(s_t, c, \gamma)$ approaches 0 so that the behavior of y_t is given by $y_t = x_t\beta + \varepsilon_t$. As s_t moves further from c, $G(s_t, c, \gamma)$ approaches 1 so that the behavior of y_t is given by $y_t = x_t(\beta + \alpha) + \varepsilon_t$.

Equations (1) and (2) can be reduced to a homogeneous model by imposing either H_0: $\gamma = 0$ or H_0: $\alpha = 0$. We test homogeneity using the null hypothesis H_0: $\gamma = 0$. To circumvent the identification problem, we replace $G(s_t, c, \gamma)$ in Equation (1) with its Taylor expansion around $\gamma = 0$, and this leads to the auxiliary equation (see Luukkonen *et al.*, 1988):

$$y_t = \sum_{k=1}^{K} \beta_k y_{t-k} + \sum_{k=1}^{K} y_{t-k} s_t \pi_1 + \sum_{k=1}^{K} y_{t-k} s_t^2 \pi_2 + \sum_{k=1}^{K} y_{t-k} s_t^3 \pi_3 + v_t \quad (33)$$

Estimating the auxiliary Equation (3), and the joint significance of the following hypothesis is tested:

H_4: $\pi_1 = \pi_2 = \pi_3 = 0$;

H_3: $\pi_3 = 0$;

H_2: $\pi_2 = 0$ $\ given \ $ $\pi_3 = 0$;

H_1: $\pi_1 = 0$ $\ given \ $ $\pi_2 = \pi_3 = 0$.

If H_0 cannot be rejected, we conclude that the linear model is suitable. Otherwise, a nonlinear model is preferable. After rejecting the linear hypothesis, the test will continue to select the specific form of $G(s_t, c, \gamma)$. In Taylor expansion of the STAR model, if H_2 has the smallest p-value, then the ESTAR process is preferable; if either H_1 or H_3 has the smallest p-value, then the ESTAR process is not preferable (see Lin & Terasvirta, 1994).

In the STAR model, a linearity test can be used to select the appropriate transition variable s_t. We carry out the test using a set of candidate transition variables, in which, we choose the variable with the strongest rejection of linearity (if any) as the transition variable.

In summary, the STAR model estimation follows these steps. Firstly, a K-order autoregressive model AR(K) is established according to Equations (1) and (2), and the appropriate lag order p-value is selected according to the AIC/SC criterion on the premise that the error term has no autocorrelation. Then, we check the linearity of the set model and determine the optimal s_t. Finally, the data are brought into a suitable STAR model for coefficient and threshold estimation.

After getting the parameter estimation for the STAR model, we resort to the STAR thresholds to extract the cyclical lengths of the estimated financial cycles. The threshold is a state transition point. It divides the financial cycle index into two parts, the low phase area to the left of the point and the high phase area to the right of the point. In fact, a low/high phase area represents the contraction/expansion phase of a national financial cycle. Therefore, through the state transition points, we can easily identify the contraction and expansion phases of the financial cycles. To capture the expansion and contraction phases of financial cycles, we define the difference between a financial cycle at the time *t* and *t-1* as:

$$\Delta_t FC^{AG} = FC_t^{AG} - FC_{t-1}^{AG} \tag{4}$$

where $\Delta_t FC^{AG}$ represents the difference between the financial cycle at the time *t* and *t-1*. The FC_t^{AG} and$\bar{t}$ are the financial cycle for the time *t* and *t-1*, respectively. When the $\Delta_t FC^{AG}$ is greater than 0, it means that the financial cycle is rising at the time t, and vice versa.

In our application, when the financial cycle is in the contraction/expansion phase at the time $t = \tilde{t}$, the financial cycle will go to rise/fall in the next phase. When this happens, we mark this time $t = \tilde{t}$ as the start of a financial cycle. Until the end of the increase/decline in the financial cycle in the next expansion /contraction phase at the time $t = \bar{t}$, we consider the time elapsed from $\tilde{t}$ to $\bar{t}$ as a financial cycle.

The search procedure of identical state transition points is applied to all estimated national financial cycles to ensure the global consistency of results. The chosen ESTAR parameters impose minimal restrictions, thus avoiding the bias towards low-frequency dynamics.

Frequency connectedness approach

This paper draws on the research of the frequency connectedness approach (see Barunik & Křehlík, 2018), which combines the spectral representation for variance decompositions (see Stiassny, 1996) and the time-domain connectedness measures (see Diebold & Yilmaz, 2012, 2014). This approach uses the Fourier transforms of the impulse-response functions and assesses shares of forecast error variation in a variable *i* due to shock to a variable *j* at a specific frequency band, so it is also known as the frequency connectedness approach. It helps us estimate the connectedness of financial cycles in short- and long-term frequency bands and disentangle the shock sources of connectedness among financial variables.

The focus of the frequency domain connectedness measurements is the GFEVD, which represents the pairwise directional connectedness from *j* to *i* and illustrates the influence the variable *j* has on the variable *i* regarding its forecast error variance share. Barunik and Křehlík (2018) combined the GFEVD with spectral representation, and the spectral representation of GFEVD can be mathematically formulated as:

$$\theta_{ij}(\omega) = \frac{(\Sigma)_{jj}^{-1}\left|(\Psi(e^{-\mu})\Sigma)_{ij}\right|^2}{(\Psi(e^{-\mu})\Sigma\Psi'(e^{+\mu}))_{ii}} \tag{5}$$

where $\theta_{ij}(\omega)$ can be used as an indicator of within-frequency and denotes the portion of the spectrum of the *i* variable due to shocks of *j* variables at a given frequency ω, $\omega \in (a, b)$. Σ is the $N \times N$ time-varying variance covariance matrix, we suppose that ε is the white noise with the covariance matrix Σ. $\Psi(e^{-\mu}) = \sum_h e^{-\mu h}\Psi_h$is the frequency response function, which is obtained from a Fourier transform of the moving average coefficients Ψ_h, and $\mu = \sqrt{-1} \cdot \omega$.

Instead of focusing solely on a single frequency, we are typically also interested in evaluating frequency connectedness on different bands in economic applications. Hence, we set a frequency band $d = (a, b): a, b \in (-\pi, \pi), a < b$, then the generalized variance decompositions on the frequency band *d* are defined as (see Barunik & Křehlík, 2018):

$$\theta_{ij}(d) = \frac{1}{2\pi}\int_d \Gamma_i(\omega)\theta_{ij}(\omega)d\omega \tag{6}$$

where $\Gamma_i(\omega) = \frac{2\pi(\Psi(e^{-\mu})\Sigma\Psi'(e^{+\mu}))_{ii}}{\sum_{h=0}^{\infty}(\Psi_h\Sigma\Psi_h')_{ii}}$ is the weighting formula by weighting$\theta_{ij}(\omega)$ through the frequency share of the variance of the *i* variable, and it represents the power of the *i* variable at a given frequency.

To improve the accuracy of the estimation, we define the standard discrete Fourier transformed cross-spectral density $\int_d \Psi(e^{-\mu})\,\Sigma\Psi^{'}(e^{+\mu})d\omega$, which is estimated as (see Barunik & Křehlík, 2018):

$$\sum_{\omega}^{\Sigma} \hat{\Psi}(\omega)\hat{\Sigma}\Psi^{'} \tag{7}$$

where $\hat{\Psi}(\omega) = \sum_{h=0}^{H-1} \hat{\Psi}_h e^{-2\pi\mu/H}$, $\hat{\Psi}(d) = \sum_{\omega} \hat{\Psi}(\omega)$ and $\hat{\Sigma} = \hat{\varepsilon}^{'}\hat{\varepsilon}/(T-z)$, in which z represents a correction for a loss of degrees of freedom.

Based on Equation (7), we can obtain the estimated generalized causation spectrum and weighting function (see Barunik & Křehlík, 2018):

$$\hat{\theta}_{ij}(\omega) = \frac{(\hat{\Sigma})_{jj}^{-1}((\hat{\Psi}(\omega)\hat{\Sigma})_{ij})^2}{(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}^{'}(\omega))_{ii}} \tag{8}$$

$$\hat{\Gamma}_i(\omega) = \frac{(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}^{'}(\omega))_{ii}}{(\sum_{\omega} \hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}^{'}(\omega))_{ii}} \tag{9}$$

In summary, we can get the estimation of the generalized variance decompositions at a desired frequency band *d*:

$$\hat{\theta}_{ij}(d) = \sum_{\omega} \hat{\Gamma}_i(\omega)\hat{\theta}_{ij}(\omega) \tag{105}$$

Here, we can construct the total directional connectedness to/from others ($TO_i/FROM_i$) and the total connectedness index (TCI) (see Diebold & Yilmaz, 2012).

$$TO_i(d) = \sum_{i=1,i\neq j}^{N} \hat{\theta}_{ji}(d) \tag{116}$$

$$FROM_i(d) = \sum_{i=1,i\neq j}^{N} \hat{\theta}_{ij}(d) \tag{12}$$

$$TCI(d) = \frac{1}{N}\sum_{i=1}^{N} TO_i(d) = \frac{1}{N}\sum_{i=1}^{N} FROM_i(d) \tag{137}$$

where $TO_i/FROM_i$ representing the variable *i* transmits/accepts its shock to/from all other variables *j*. TCI can be obtained from the average total directional connectedness from (to) others, indicating the degree of network interconnectedness and market risk.

Results

The persistence of financial cycles

According to Borio (2014), the formation of national financial cycles is self-reinforcing interactions among perceptions of value and risk, risk perception, and financing constraints. Thus, differences in national financial environments shape differences in national financial cycles. National financial cycles are closely linked to the global financial cycle, but have relative independence. In this section, we explore the existence and persistence of national financial cycles to investigate the inter-country differences and global universal features, and also to provide a premise for further exploration of financial cycle spillover linkages.

Estimated financial cycles

We estimate aggregate financial cycles for each country, including smoothed version and unsmoothed version cycles. However, estimation of financial cycles is hindered by the availability of sufficiently long historical series. For some countries, when a certain cycle length is especially short or a longer sample timespan, there will be multiple cycles within the sample time. At this time, a cycle length in the middle position among all cycle lengths is selected as the national financial cycle.

Table 3 shows the persistence of de-trended and standardized aggregate financial cycles, organized by region and country ISO3 for ease of navigation. As seen in Table 3, the sample countries have distinct and varying persistence in financial cycles. At the same time, this result implies a significant mean-reversion and asynchronous phenomenon of financial cycles. Financial cycles are associated with the accumulation of market imbalances and their subsequent correction, and persist for 13.3 years for smoothed and 8.7 years for unsmoothed on average, which is far below the frequency of the business cycle (the business cycle involves frequencies from 1 to 8 years) (see Yan & Huang, 2020; Trotta Vianna, 2023). Smoothed cycles emphasize the lower frequency dynamics, picking up only major episodes of systemic market distress. Hence, the ESTAR algorithm also yields a lower count of turning points in comparison with the unsmoothed cycles.

Estimated financial phases

Further, based on the smoothed aggregate financial cycle data, we calculate the persistence and amplitude of different phases in each country to observe the characteristics and differences of national financial cycles in a more detailed and multi-dimensional manner. As shown in Table 4, the persistence and amplitude of the smoothed global financial cycle and national financial cycles are asynchronous in both the contraction and expansion phases. It indicates that the global financial cycle is not a simple superposition of national financial cycles. Financial cycles tend to have an asymmetric "sawtooth" shape with relatively more prolonged expansions and faster contractions on average.

In terms of persistence, the average contraction phase lasts longer than the expansion phase in the BEL, CAN, FIN, IDN, JPN, MYS, SWE, and USA, and the opposite is true in other countries. The North American and Southeast Asian countries have more prolonged contraction than expansion phases. With consideration of amplitude, the contraction amplitude is larger than the expansion amplitude in the AUS, CHE, FRA, IDN, ITA, JPN, and MYS, and the opposite is true for other countries. In parallel, developed countries tend to have short financial cycles and high volatility. This reminds us that more frequent and unstable financial fluctuations in developed countries may cause more pronounced financial contagion. Furthermore, we compare the amplitude differences between contraction and expansion phases for the same country. Except for the JPN, the other developed countries have several same amplitudes during contraction and expansion phases. It indirectly confirms that financial cycles proceed in tandem, sometimes at different speeds and in different phases on a global scale (see Borio, 2014). Also, it reveals that economic development is a crucial factor affecting financial cycles (see Pineda *et al*., 2022).

Based on the above analysis, we have some ideas about cycle persistence, phase, and amplitude. However, we are also concerned with the external influences on a national financial cycle, the main drivers of the global financial cycle, and the relationship between the global financial cycle and economic development. Therefore, the next section will focus on this.

The connectedness of financial cycles

The study in the previous section told us about the characteristics of financial cycles, but this is insufficient to support our understanding of the critical impact of financial cycles on mutual contagions and economic development. In this section, we further explore the dynamic connectedness of financial cycles and their frequency decomposition using the unsmoothed aggregate financial cycle index from 1991Q1 to 2014Q4. We draw on the frequency connectedness approach to extract dynamic connectedness and calculate the connectedness for the high- and low-frequency bands, which relate to the short-term and long-term horizons.

Total connectedness of financial cycles

Figure 2 displays the detailed dynamics of the total connectedness of national aggregate financial cycles determined by frequency-domain variance decompositions. We decompose the financial connectedness into two frequency bands, 1–17 quarters (short-term) and more than 17 quarters (long-term), according to the persistence of the average unsmoothed financial phase in Table 3.

As seen in Figure 2(b), the TCI of the aggregate financial cycles is high, showing time-varying magnitudes that fluctuate more than 80%, implying increased risk in financial markets. Moreover, the frequency connectedness of financial cycles is highly dependent on financial events, with the most prominent peak near the end of the 1990s (the Asian financial crisis) and around 2007–2009 (the global financial crisis). In addition, some important events also make the total connectedness reach a local peak. For example, the dot com bubble and the September 11 terrorist attacks made the TCI reach a local peak near 2001. In the aftermath of the global financial crisis, central banks in the USA and the GBR adopted unconventional monetary policy tools to bring down the risks and shocks, such as quantitative easing and forward-looking rates (see Polat, 2022). Following government intervention, the TCI declined. In contrast, near 2011, the European debt crisis caused a rebound in systemic risk, which led to a rebound in total connectedness. The above phenomenon illustrates that the linkages among national financial cycles increase due to financial crises, policy moderation and global imbalances (see Park & Shin, 2020; BenSaïda & Litimi, 2021; Qin *et al*., 2021). In addition, many national financial events have a significant impact on a country or a region but have little global impact and therefore. are not evident in the graph. Overall, the shocks to worldwide financial cycles are highly correlated with the financial connectedness effect, and that connectedness is a manifestation of risk.

Comparing Figure 2(a) and Figure 2(b), we find that after the financial crisis broke out in late 2007, the global financial cycle declined rapidly, while the TCI continued to strengthen until early 2009, indicating that the financial connectedness further deepens the persistence and harmfulness of financial shocks. After a highly unpredictable and chaotic period, market risk gradually decreased and stabilized, and the TCI achieved its lowest values around 2004 and 2014. It indicates that the connectedness of financial cycles also has a pronounced cyclical nature, and the persistence between the two peaks/valleys is about 9 years, which is highly consistent with the average persistence of the national financial cycles obtained in the previous section.

Shocks from specific financial events allow us to clearly understand the time-varying process of the financial markets' connectedness, but cyclical elements will inevitably produce heterogeneous shocks resulting in various sources of connectedness and thus short- and long-term systemic risk (Denkowska & Wanat, 2020). It is necessary to understand whether shocks originate in the short- or long-term, which is also a way to understand the propagation cycle of shocks (see Engle & Granger, 1987; Dew-Becker & Giglio, 2016). Figure 2(c) reveals that, in most cases, the evolutionary dynamics of the connectedness are mainly driven by short-term components. It indicates that financial market participants tend to expect that uncertain future shocks will have short-term impacts and are more confident of the long-term stability of the financial system (see Barunik & Křehlík, 2018). The response of the financial events (transmission of intra-network shocks) is mainly in the short term, and the financial events that occurred before 17 quarters have less impact on the current financial market. In contrast, during 1998–1999, long-term connectedness played a dominant role, driving the total connectedness to a peak and increasing the systemic risk. This may be due to the successful shift in monetary policy in many Asian countries from the de facto pegs to floating currencies in the aftermath of the Asian financial crisis (see Arndt & Hill, 1999). It shifted investors' expectations that only became apparent much later.

Although the above analysis exposes the dynamic evolution of the financial cycles and decomposition in the short- and long-term, it does not allow us to clarify which countries are driving or driven by financial risks. Therefore, we proceed to investigate the interconnectedness network that causes financial cycle changes.

Interconnectedness networks

Figure 3 summarizes the interconnectedness network for national financial cycles. In the figure, when a country's total directional connectedness to others is more than from others, we call it the net transmitter, hence driving the interconnectedness network. Conversely, we call it the net receiver and hence driven by the network. From Figure 3(a), the NLD, KOR, FIN, GBR, HUN, CAN, FRA, BEL and USA are the net transmitters, and the AUT, THA, CHE, JPN, ITA, SWE, AUS, MEX, IDN, NOR, MYS, ESP, PHL, CHN, SGP are the net receivers, ranked by degree of drive/driven. The largest net transmitters and net receivers are the NLD and AUT, respectively. Combined with the persistence of financial cycles, we find that the financial cycle lengths of net transmitters are generally shorter than average, and conversely, net receivers have longer financial cycles. Some studies consider the USA as the largest net transmitter globally, but our study does not obtain such a result. This may be because we utilize aggregate financial cycles, which produce different findings than using segment-specific financial market cycles. The degree of openness, financial system stability, economic bubble and financing constraints will affect a country's net total directional connectedness (see Huang, 2020). Thus, in general, developed countries act as net transmitters and developing countries as net receivers, moreover, the connectedness between developed countries is stronger than that between developing countries. From Figure 3(b-d), we find that the broader lines are more likely to connect countries in the same region, meaning that the cross-country connectedness within the region is more pronounced than across regions. Separately, the largest transmitter of risks in the American region is the CAN. In this region, the CAN mainly influences Asian countries, while the USA has closer ties with European countries. The most significant risk transmitter in the Asian region is the KOR, and the interconnectedness of the East Asian region is stronger than that of Southeastern Asian region. The largest risk transmitter in the European region is the NLD, which is consistent with the study of Umar *et al*. (2021). Although not all countries are connected as described above, we can find extreme interconnectedness between some countries within regions, such as KOR-SGP, CHN-PHL, FRA-FIN, HUN-GBR and NLD-HUN. It is not surprising that the establishment of regionally integrated markets and regional cooperation mechanisms, such as the North American Free Trade Agreement, Euro Convergence Criteria and ASEAN Economic Community, have facilitated the regional economic integration and the crisis of the same origins (see Zimmerman & Stone, 2018; Wu, 2020).

Regarding the frequency decomposition of the interconnectedness network, as seen in Figure 4, the cross-country connectedness is mainly driven by short-term components. Most countries as short-term net transmitters/receivers are consistent with the conclusions obtained from Figure 3. However, in the long-term, the driving and driven countries of systemic risks significantly differ from those in Figure 3. In the short-term, the most significant transmitter of risk in the American region is the USA, while in the long-term is the CAN. The strongest Asian region's risk driver is the KOR in both the short- and long-term. In the European region, the NLD is the largest net transmitter in the short-term, while in the long-term is the ESP. The interconnectedness network helps policymakers effectively identify the primary sources of external risk shocks as well as track and prevent international risk shocks in the short- and long-term.

Global financial cycle and economy

Financial cycles can be characterized as a manifestation of the interplay among global liquidity conditions, risk perceptions and increasing financial connectedness, giving rise to capital flows and spillovers from systemic economies to the rest of the world (see Mei *et al*., 2020). In order to trace the causes of global financial cycle movements and the relationship with business cycles, we compare trends in the global financial cycle, total connectedness, risk perception, global liquidity and global economic developments. We use the CBOE VIX to evaluate global risk and uncertainty (see Adarov, 2022), the TED spread is used to measure short-term liquidity (see Pineda *et al*., 2022), and the ADS as an indicator of global economic status (see Aruoba & Diebold, 2009).

As shown in Figure 5(a), the movements of the TCI, TED spread and VIX index show strong synchronized fluctuations, especially around the financial crisis. This is because the worse the financial environment is, the higher the panic, the tighter the liquidity, and the closer the interconnectedness. Combined with Figure 5(b), the GFC continued to grow until the financial crisis broke out in late 2007 and then began to decline, but after that, the TCI, TED spread, and VIX continued to exhibit strong upward movements until late 2009. It illustrates that the financial cycle generates a rapid downward response after a financial event, while TCI, TED spread, and VIX continue to accumulate and deepen shocks over a while (see Mei *et al*., 2020; Adarov, 2022). It also proves that the USA plays a driving role in the diffusion of financial shocks, because the VIX index and TED spread are influenced by the USA stock market and monetary policies (see Li *et al*., 2021; Polat, 2022). Moreover, we find that the persistence of the global financial cycle is longer than the business cycle, which is consistent with the study of Borio (2014), Borio *et al*. (2019), and Skare and Porada-Rochon (2020). Besides, the financial fluctuations precede the business fluctuations during the financial events because an increase in the systemic financial risk could lead to a severe macroeconomic dislocation (see Li *et al*., 2021). It implies that policymakers should consider the financial system before bailing out the real economy, which alone is insufficient for recovering the macroeconomy (see Shen *et al*., 2018).

Discussion

The purpose of this paper is to give a more comprehensive understanding of the characteristics and effects of the financial cycles. Through the empirical analysis, we obtain the general characteristics and individual differences of financial cycles on a global scale, followed by a discussion of the total and direction connectedness of financial cycles and the relationship with the economy.

Financial cycles persist for 13.3 years for smoothed and 8.7 years for unsmoothed on average. It is far below the frequency of the business cycle and tends to have asymmetric rates of expansion and contraction, which is consistent with the findings in Borio (2014) and Adarov (2022), but more generally because a broader sample and aggregated indices are utilized. Besides, it emphasizes the unsustainability of financial market developments, the continuous accumulation of financial imbalances, and the rapid destruction of financial recession. The relevant conclusions can help policymakers and managers recognize and understand the characteristics of the financial cycles and the financial system before bailing out the real economy (see Shen *et al*., 2018).

However, this paper does not discuss what policies should be implemented before/during the contraction and expansion phases. For that matter, some research suggests that monetary policy is effective in reducing market overheating, but may be cost prohibitive (see Filardo *et al*., 2022). Therefore, it is necessary to build up buffers in good times and allow central banks to tighten so as to lean against the build-up of financial vulnerabilities (see Borio, 2011). There is also the opposite conclusion that monetary tightening makes asset prices bubblier (see Galí *et al*., 2021). Nevertheless, it is reasonable to implement monetary policy when macroprudential policy effectiveness is imperfect (see Gourio *et al*., 2018).

This research also reveals the cross-country and cross-regional interconnectedness of financial cycles. It is highlighted that the interconnectedness of financial cycles is mainly influenced by the systematic shocks in developed countries in the short-term, which is in line with the mainstream view (see Park & Shin, 2020; BenSaïda & Litimi, 2021; Qin *et al*., 2021). The difference is that the largest net transmitter is the NLD in our results, while many studies consider the USA. If only the European region is observed, consistent findings can be found from previous studies (compare Umar *et al*., 2021).

Anyway, our study carves out the total connectedness, spillover paths, and sources of risks of the global financial cycle. Although we do not additionally discuss how to avoid the negative effects of interconnectedness, based on our findings it is known that policymakers should pay close attention to emerging trends in finance domestically, regionally and in highly interconnected countries, and actively pursue financial regulation and risk prevention to restrain the build-up of financial imbalances. Specifically, national governments should pay close attention to the abnormal fiscal and monetary policies of major net spillover countries and adopt relative policies to hedge against them to defuse financial bubbles and minimize the negative effects of financial crises (see Strohsal *et al*., 2019; Polat, 2022). In addition, national government authorities should strengthen policy coordination and actively search for the optimal equilibrium between domestic policies and the global financial market to reduce the external spillover effects and maximize overall social welfare.

Conclusions

In the trend of globalization, the linkage of global financial markets, the connectedness of financial fluctuations and the spread of market imbalances have attracted widespread attention, especially after the financial crisis. In order to comprehensively and accurately portray the characteristics of financial cycles and the complex network of mutual contagion, this paper investigates the mean reversion and persistence of financial cycles in 24 countries around the world using the nonlinear STAR model. Furthermore, we study the total and cross-country connectedness of financial cycles using the frequency connectedness approach and discuss the relationship between the global financial cycle and total connectedness, risk perception, global liquidity and economic developments.

Our study finds that financial cycles are generally mean reversion but asynchronous, and persist for 13.3 years for smoothed aggregate financial cycles and 8.7 years for unsmoothed on average, well below the duration of the business cycle. The amplitudes of national financial cycles tend to have an asymmetric "sawtooth" shape with relatively more prolonged expansions and faster contractions. Developed countries tend to have shorter financial cycles and higher volatility than developing countries.

The connectedness of financial cycles is influenced by systematic shocks, and contributes to the persistence and harmfulness of market shocks. It is mainly driven by the short-term component, but long-term connectedness may dominate when government intervention. Developed countries are the main net transmitters of risk, while developing countries generally act as the net receivers. The drivers of regional systemic risk are different in the short- and long-term, and the cross-country connectedness within regions is more pronounced than across regions. During the financial crisis, the global financial cycle movements precede and are longer than business fluctuations.

During the COVID–19 pandemic, the global systemic risk interdependence has become increasingly high. Given this, policymakers should correctly understand the relationship between the business cycle and financial cycle, pay attention to new financial trends in domestic, regional, and highly interconnected countries, actively carry out financial regulation and risk prevention, and adopt appropriate monetary and macroprudential policies to mitigate financial imbalances.

Of course, this study has certain limitations. The sample is unevenly distributed, with little data from Eastern and Southeastern Europe and no coverage of South America, Africa and the Middle East. And we do not consider the cyclical performance of segment-specific financial markets and the cross-market connectedness between segment-specific and aggregate financial cycles. Future research can be improved in this direction. In addition, additional research can be conducted on how specific monetary policies affect the financial cycle, thus providing a reference for the establishment of a reliable and practical macroprudential system.

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Annex

Table 1. Sample and code

America (AME)	Asia (ASI)	Europe (EUR)
Canada (CAN), Mexico (MEX), The United States (USA)	Australia (AUS), China (CHN), Indonesia (IDN), Japan (JPN), South Korea (KOR), Malaysia (MYS), Philippines (PHL), Singapore (SGP), Thailand (THA)	Austria (AUT), Belgium (BEL), Switzerland (CHE), Spain (ESP), Finland (FIN), France (FRA), The UK (GBR), Hungary (HUN), Italy (ITA), The Netherlands (NLD), Norway (NOR), Sweden (SWE)

Table 2. Summary statistics of quarterly aggregate financial cycle index

Unsmoothed	**AUS**	**AUT**	**BEL**	**CAN**	**CHE**	**CHN**	**ESP**	**FIN**	**FRA**	**GBR**	**HUN**	**IDN**
Time span	1976Q2-2015Q4	1971Q1-2015Q4	1986Q2-2014Q4	1980Q3-2014Q4	1981Q4-2014Q4	1991Q4-2015Q4	1986Q1-2014Q4	1990Q4-2012Q4	1979Q1-2015Q4	1981Q4-2014Q4	1993Q1-2015Q4	1991Q2-2014Q4
Min	-2.35	-2.99	-2.11	-2.88	-1.48	-1.61	-1.43	-1.51	-1.45	-2.13	-2.76	-2.64
1stQu	-0.75	-0.60	-0.63	-0.56	-0.51	-0.81	-0.89	-0.84	-0.85	-0.76	-0.68	-0.51
Median	0.12	-0.13	-0.12	-0.08	-0.17	0.20	-0.01	-0.07	-0.14	0.05	0.06	-0.18
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3rdQu	0.66	0.63	0.70	0.39	0.42	0.65	0.75	0.62	0.75	0.82	0.87	0.30
Max	2.36	2.75	2.42	2.45	3.26	2.38	1.94	2.41	2.46	2.09	1.57	3.85
Smoothed	AUS	AUT	BEL	CAN	CHE	CHN	ESP	FIN	FRA	GBR	HUN	IDN
Min	-2.13	-2.33	-1.65	-1.60	-1.68	-1.56	-1.45	-1.60	-1.24	-1.93	-1.88	-1.34
1stQu	-0.76	-0.74	-0.78	-0.61	-0.70	-0.88	-0.92	-0.74	-0.80	-0.80	-0.91	-0.89
Median	0.23	0.09	-0.06	-0.13	-0.10	0.36	-0.09	0.20	-0.27	0.07	-0.09	-0.19
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3rdQu	0.75	0.86	0.51	0.69	0.67	0.53	0.71	0.46	0.54	0.99	0.81	0.80
Max	1.69	1.66	2.32	2.57	2.16	2.47	1.79	2.97	2.78	1.42	1.62	2.02

Table 2. Continued

Unsmoothed	**ITA**	**JPN**	**KOR**	**MEX**	**MYS**	**NLD**	**NOR**	**PHL**	**SGP**	**SWE**	**THA**	**USA**	**Global**
Time span	1982Q3-2014Q3	1981Q4-2014Q4	1991Q4-2014Q4	1987Q3-2014Q4	1982Q4-2014Q4	1990Q4-2013Q1	1984Q1-2014Q4	1990Q4-2014Q4	1979Q1-2013Q2	1982Q1-2015Q3	1990Q4-2014Q4	1971Q1-2015Q4	1982Q3-2012Q2
Min	-2.26	-1.74	-1.76	-2.11	-2.59	-1.95	-1.85	-1.91	-2.07	-2.37	-2.43	-2.71	-1.78
1stQu	-0.7	-0.67	-0.76	-0.71	-0.37	-0.59	-0.65	-0.76	-0.8	-0.71	-0.15	-0.65	-0.76
Median	-0.14	-0.07	0.17	-0.09	0.08	-0.24	-0.19	0.09	0.05	0.09	0.15	0.23	-0.02
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3rdQu	0.86	0.5	0.75	0.64	0.41	0.73	0.73	0.55	0.53	0.71	0.76	0.64	0.67
Max	1.89	1.85	1.73	2	2.31	2.02	2.15	1.82	2.74	2.12	1.33	2	2.39
Smoothed	ITA	JPN	KOR	MEX	MYS	NLD	NOR	PHL	SGP	SWE	THA	USA	Global
Min	-1.82	-1.43	-1.49	-1.70	-1.40	-2.29	-2.03	-1.86	-1.88	-2.07	-2.00	-2.45	-1.89
1stQu	-0.79	-0.75	-0.96	-0.92	-0.77	-0.90	-0.58	-0.76	-0.87	-0.65	-0.66	-0.45	-0.86
Median	-0.05	-0.24	0.04	0.16	-0.26	-0.02	0.21	0.25	0.10	0.16	0.19	0.15	0.2
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3rdQu	0.91	0.69	0.85	0.85	0.70	0.71	0.74	0.57	0.75	0.70	0.88	0.69	0.73
Max	1.60	2.60	1.88	1.42	2.42	1.72	1.99	1.71	1.53	1.83	1.15	2.57	1.79

Source: both smoothed and unsmoothed data are from Adarov (2022).

Table 3. The average persistence of the national financial cycle

Region	Country	Observations	Smoothed financial cycles		Unsmoothed financial cycles	
			Persistence (quarter)	Persistence (year)	Persistence (quarter)	Persistence (year)
AME	CAN	138	43	10.75	28	7
	MEX	110	63	15.75	24	6
	USA	180	41	10.25	29	7.25
ASI	AUS	159	72	18	35	8.75
	CHN	97	/	/	61	15.25
	IDN	95	51	12.75	15	3.75
	JPN	133	38	9.5	36	9
	KOR	93	/	/	34	8.5
	MYS	129	36	9	27	6.75
	PHL	97	/	/	37	9.25
	SGP	138	64	16	40	10
	THA	97	/	/	36	9
EUR	AUT	180	45	11.2	37	9.25
	BEL	115	37	9.25	30	7.5
	CHE	133	79	19.75	31	7.75
	ESP	116	70	17.5	74	18.5
	FIN	89	/	/	32	8
	FRA	148	43	10.75	32	8
	GBR	133	58	14.5	38	9.5
	HUN	92	/	/	32	8
	ITA	133	66	16.6	31	7.75
	NLD	90	40	10	26	6.5
	NOR	124	58	14.5	31	7.75
	SWE	135	50	12.5	39	9.75
Global		121	72	18	42	10.5
Average		123	53.3	13.3	34.8	8.7

Note: due to the limitation of data availability, the complete financial cycle as we define it in Section 2 does not appear for some countries.

Source: own calculations based on data from Adarov (2022).

Table 4. The average persistence and amplitude of financial phases

Region	Country	Observations	Expansion phase		Contraction phase	
			Persistence	Amplitude	Persistence	Amplitude
AME	CAN	138	20	3.66	23	3.56
	MEX	110	33	2.84	30	3.11
	USA	180	20	/	21	3.99
ASI	AUS	159	47	3.3	25	3.8
	CHN	97	35	2.11	/	/
	IDN	95	19	3.16	32	3.34
	JPN	133	15	0.73	23	2.74
	KOR	93	/	/	/	/
	MYS	129	16	3.29	20	3.82
	PHL	97	/	/	25	3.55
	SGP	138	33	3.39	31	2.59
	THA	97	/	/	27	3.14
EUR	AUT	180	23	3.98	22	3.94
	BEL	115	16	1.66	21	1.59
	CHE	133	51	2.49	28	3.81
	ESP	116	42	3.22	28	2.89
	FIN	89	42	2.12	/	/
	FRA	148	17	2.94	26	3.3
	GBR	133	34	3.34	24	3.06
	HUN	92	/	/	43	2.69
	ITA	133	40	3.15	26	3.4
	NLD	90	22	/	18	1.97
	NOR	124	29	2.83	15	0.62
	SWE	135	24	3.89	26	2.88
Global		121	47	2.62	25	3.48
Average		123	29.76	2.88	25.41	3.06

Note: the persistence of the expansion (contraction) phase is the number of quarters between the trough and the peak (the peak and the trough). The amplitude is the difference between the peak and the trough.

Figure 1. Research framework

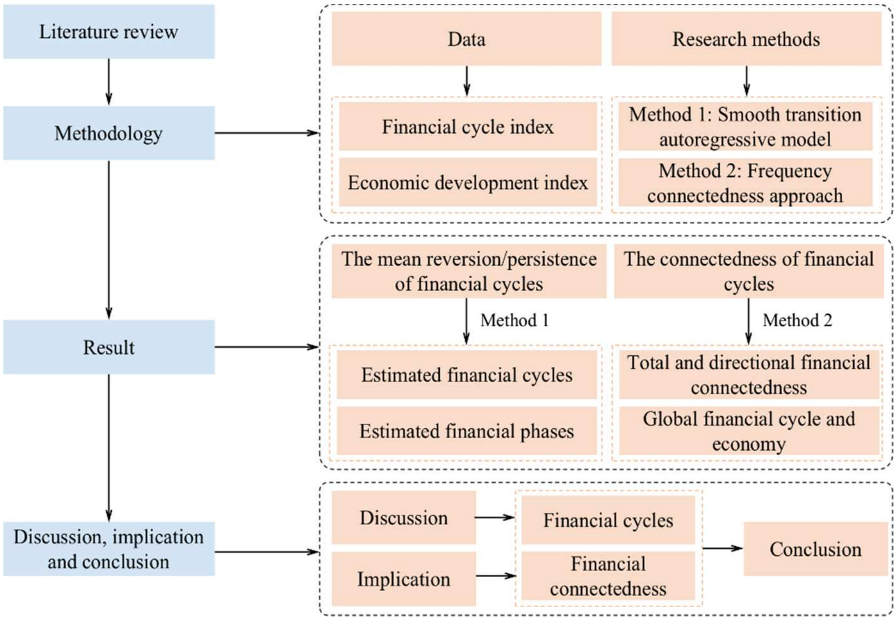


Figure 2. Global financial cycle and total connectedness index

(a) Global financial cycle

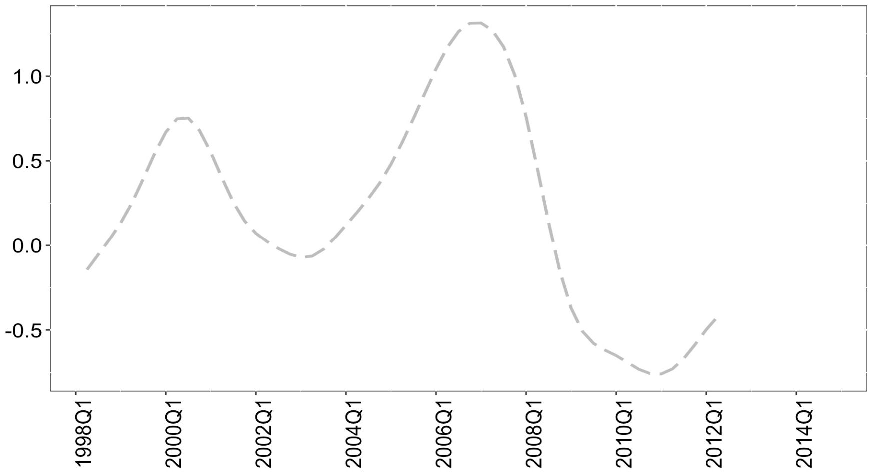
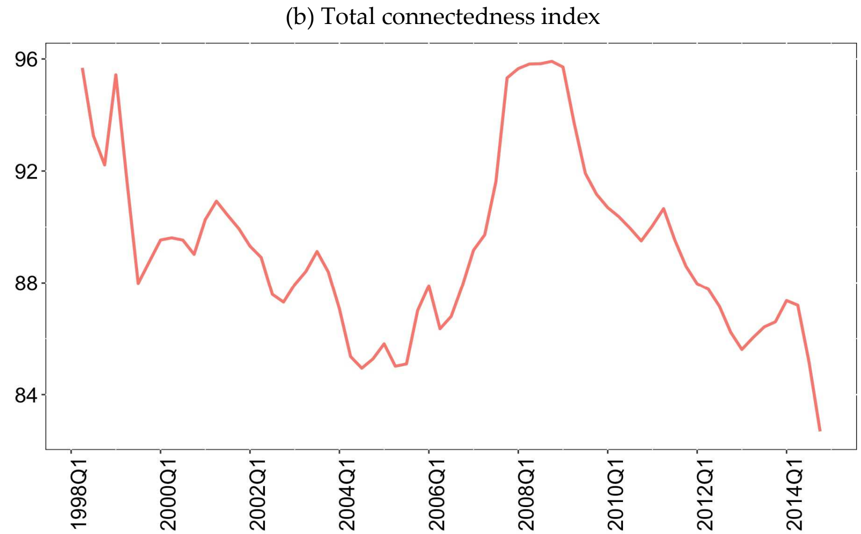
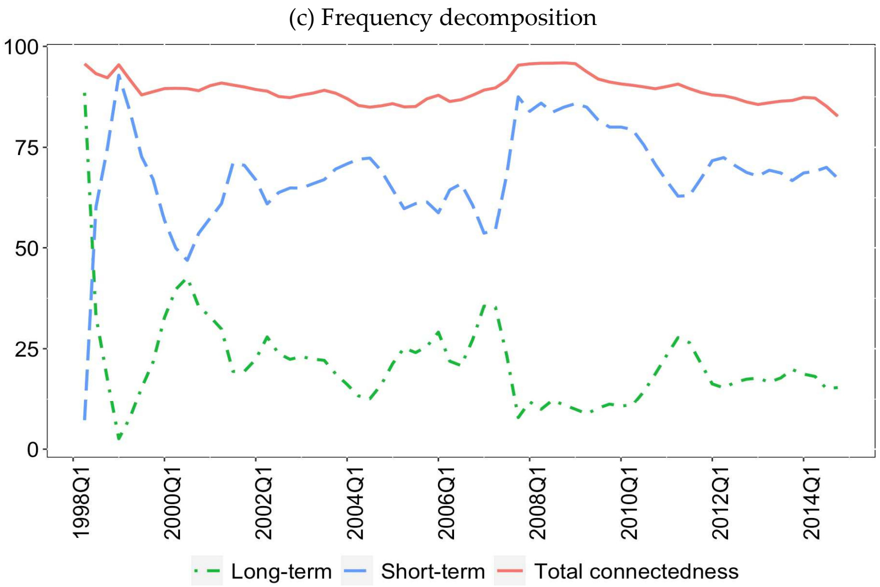


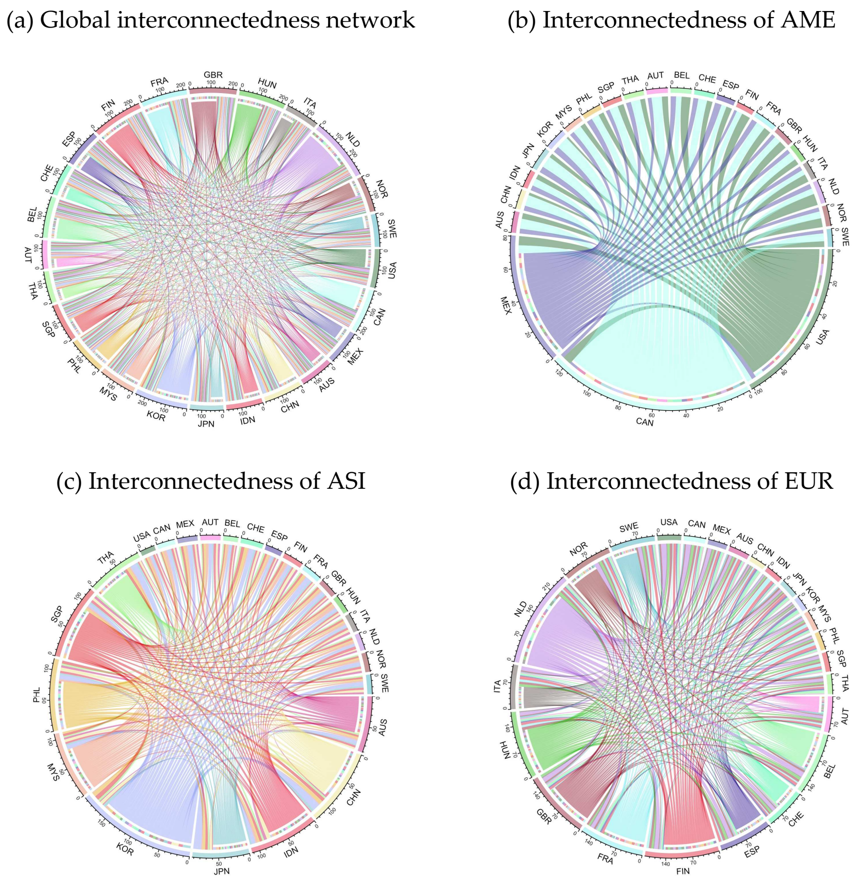
Figure 2. Continued





Note: the total connectedness index (TCI) illustrates the degree of global financial markets connectedness and its risk. Panel (a) shows the global financial cycle (grey long-dash line), Panel (b) shows the overall evolution of the total connectedness index (red solid line), and Panel (c) shows the frequency decomposition of TCI, in which the blue long-dash and green dot-dash lines indicate the frequency connectedness in the short-term (1–17 quarters) and long-term (more than 17 quarters), respectively.

Figure 3. The interconnectedness of aggregate financial cycles

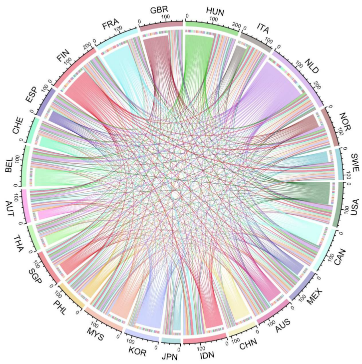


Note: the bar charts on the outer circle indicate the individual countries with different colors, and the width of the nodes and connected lines indicate the degree of connectedness. In the inner circle, the lines with the same/different color as the bar charts show the directional connectedness to/from others. If the total directional connectedness to others is more/less than from others, we call it the net transmitter/receiver. Panel (a) shows the directional connectedness network of global, and Panels (b)-(d) are obtained by splitting Panel (a) to represent the directional connectedness of regions.

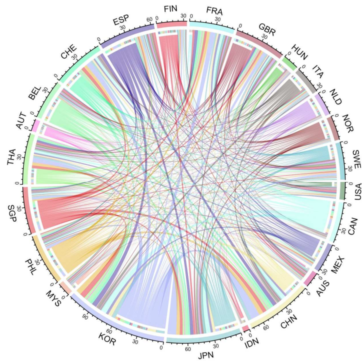
Source: own calculations by using the chordDiagram package in R software.

Figure 4. The frequency decomposition of the interconnectedness network

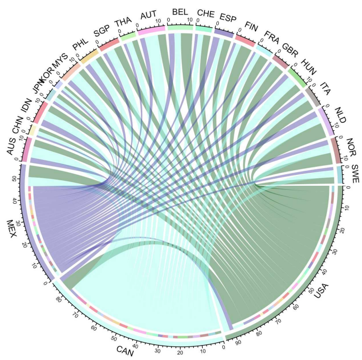
(a) Global interconnectedness network in the short-term



(b) Global interconnectedness network in the long-term



(c) Interconnectedness of AME in the short-term



(d) Interconnectedness of AME in the long-term

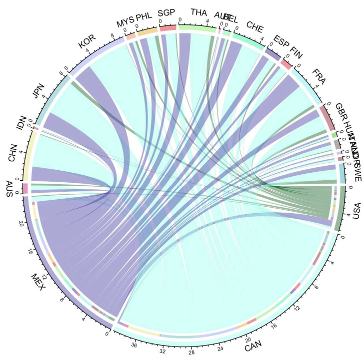
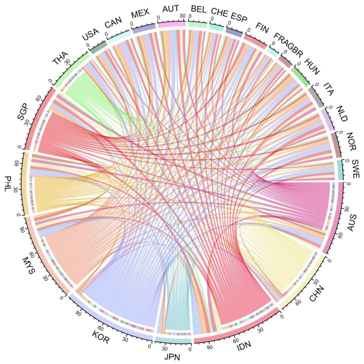
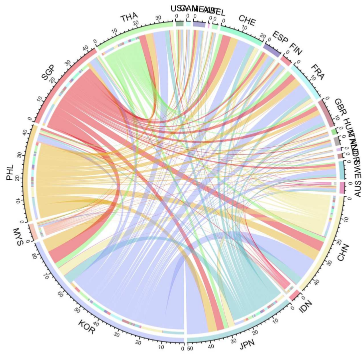


Figure 4. Continued

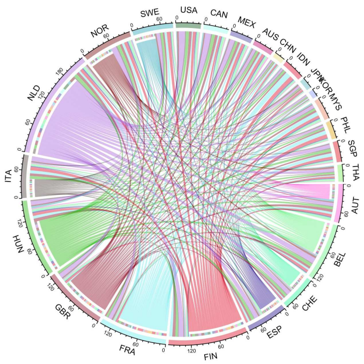
(e) Interconnectedness of ASI in the short-term



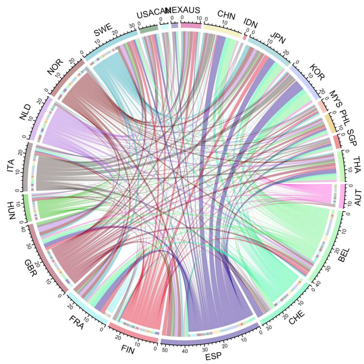
(f) Interconnectedness of ASI in the long-term



(g) Interconnectedness of EUR in the short-term

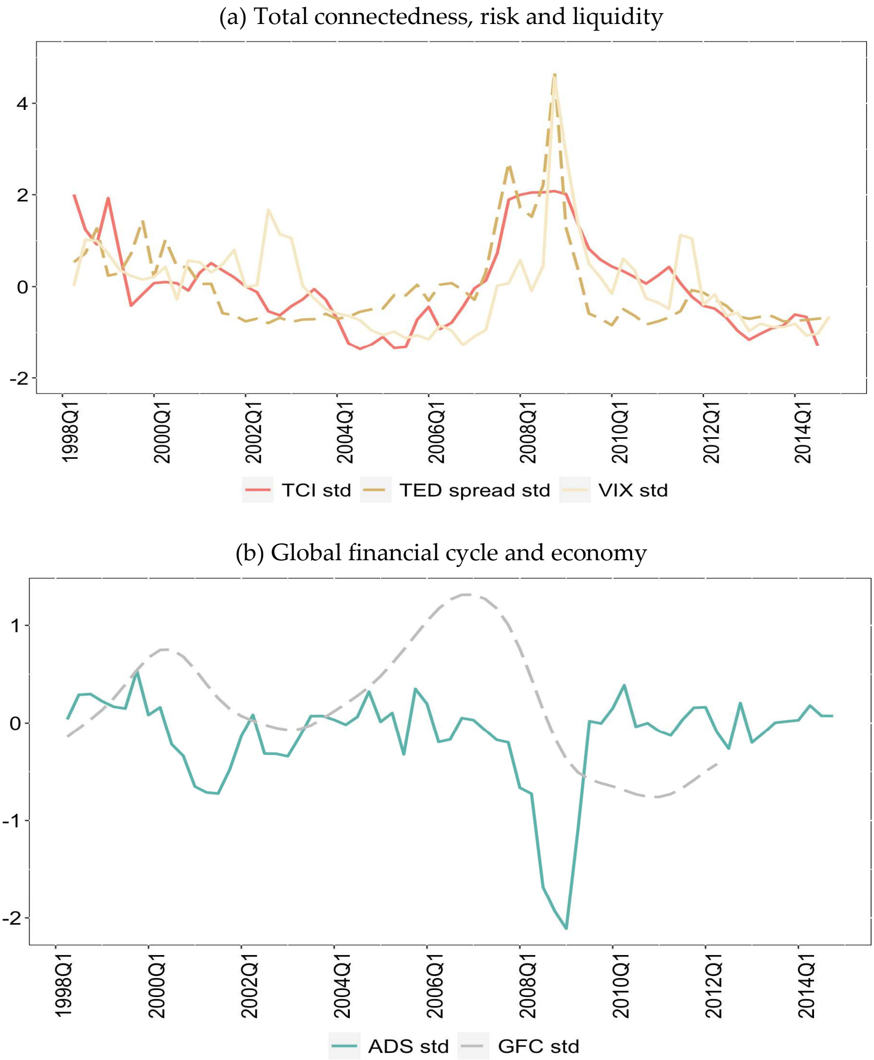


(h) Interconnectedness of EUR in the long-term



Source: own calculations by using the chordDiagram package in R software.

Figure 5. Global financial cycle and economy



Note: panel (a) compares the total connectedness, the TED spread calculated as the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill, and the VIX index that measures market expectation of near-term volatility conveyed by stock index option prices. Panel (b) shows the global financial cycle (GFC), and the ADS index that aggregates employment, production, sales, real GDP and other relevant economic indicators. All variables are standardized to make comparisons more straightforward.

Source: own calculations based on the Federal Reserve Bank of Philadelphia and Federal Reserve Economic Data.