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*Research article*

# Impact of Chinese financial shocks: A GVAR approach

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**Abstract:** This article analyzes the influence of Chinese financial shocks on emerging and advanced economies using a GVAR (Global Vector Autoregressive) from 1985Q4 to 2016Q4. We summarize our findings in five points: i) adverse shocks in Chinese financial markets can cause a global recession; ii) these shocks trigger the "flight to quality", leading to the depreciation of domestic currencies to the U.S. dollar; iii) stock and exchange markets contribute to transmitting the shock to domestic economies; iv) commodity prices are sensitive to these shocks; v) the impact of the Chinese financial shock increased in the new millennium. Finally, the financial system of China has the potential to provoke worldwide macroeconomic fluctuations.

**Keywords:** financial system; credit; exchange rate; GDP; China

**JEL Code:** E37, E44, G01

## 1. Introduction

In economics, the analysis of fluctuations in macroeconomic variables involves applying shocks to relevant economies. Often, researchers examine shocks originating from the U.S. (Kim, 2001; Chudik and Fratzscher, 2011). However, with China's growing economic influence, there is an emerging trend of studies exploring the impact of Chinese shocks on other regions (Wall and Eyden, 2016).

This article contributes to the increasing interest in comprehending Chinese shocks and their effects on the global economy. We analyze Chinese financial shocks, examining how they propagate throughout the system. Specifically, we seek to observe the behavior of emerging market economies (EMEs) and advanced economies (ADs) following these shocks. Additionally, we aim to detect transmission channels that elucidate how financial shocks impact the real sector.

We use the GVAR to generate econometric estimates model enables us to integrate the international environment into the analysis, serving as a proxy for the vulnerability of economies to external shocks. The GVAR has the advantage of allowing each region to be modeled according to its idiosyncratic factors. Furthermore, this model employs bilateral trade to establish connections between each region. As China's trade patterns with other economies have undergone significant changes over time, we can compare Chinese shocks in different periods based on trade evolution and integration. In summary, the GVAR is well-suited for studying spillover effects.

The results indicate that a negative credit shock in China induces a global recession, with the exchange rates serving as the primary transmission channel. This shock generates a widespread "flight to quality", redirecting capital to safer havens, particularly the U.S. economy.

The second Chinese financial shock was on its exchange rate, and the results closely mirrored those of the credit shock. The distinction lay in the transmission channel, where the stock market played a role in connecting the financial market with the real sector. All shocks affected variables in both emerging and advanced economies, particularly GDP (Gross Domestic Product).

We also found that the Chinese influence varied based on bilateral trade. When comparing shocks using bilateral trade data from 1985, 1995, 2005, and 2014–2016, we observed that shocks from the new millennium had a more significant impact on the world economy. This finding remained consistent even when we analyzed commodity prices. However, while the disparity in shocks between the two millennia is noteworthy, such a difference is no longer evident when assessing shocks within the same millennium.

The primary contribution of this article is its focus on the Chinese financial shock. Generally, studies examining the impact of Chinese shocks on the world economy concentrate on the real sector, particularly GDP shocks (Wall and Eyden, 2016; Çakir and Kabundi, 2017). While we build upon these works to understand how the Chinese influence evolves over time, our contribution lies in advancing the study by specifically investigating Chinese financial shocks. We aim to enrich the literature by exploring how Chinese financial markets can influence other regions and impact their financial and real sectors.

Zhang et al. (2021) investigated financial risk in China without considering the international economy, implicitly modeling China as a closed economy. Other econometric specifications, such as the VAR (Vector Autoregressive) and TVP-VAR-SV (TVP: Time-Varying Parameter, VAR: Vector Autoregressive, SV: Stochastic Volatility), incorporate Chinese financial variables with other relevant factors, but neglect to treat China as a country integrated into the international economy (Ogawa and Luo, 2022; Du et al., 2022). VAR models use relevant variables to proxy the external environment without explicitly modeling the world economy. Shehzad et al. (2021) analyzed two countries, the U.S. and China, using a VARX. However, their model included only two countries and a limited number of financial variables. We complement these studies by employing a model with 33 countries, explicitly modeling the world economy through domestic variables for each region and transmission channels. This approach allows us to understand how Chinese financial shocks spread throughout the system. In summary, our estimation strategy treats China as a region integrated into the international economy.

Some studies link the financial cycle of China with relevant economies, including the U.S., the U.K., Japan, and the Eurozone (Cheung et al., 2005; Ma and Zhang, 2016). Jiang et al. (2021) demonstrated spillovers from China's real estate sector to its economy, and Min et al. (2021) illustrated how Chinese bank credit affects the country. Both papers confine China's influence to specific regions, whereas we investigate the spillover effects of the Chinese financial system on the entire world, examining credit and exchange rate shocks.

Adarov (2020) studied a sample with a size similar to ours. He concluded that global financial cycles align with the movements of the U.S. T-bill and the VIX index, and BenSaida and Litini (2021) focused on the Eurozone. Considering the significant growth of China's importance in the world economy, we hypothesize that the Chinese financial system could trigger pronounced international fluctuations.

Many articles employed the GVAR to explore international connections among countries. Bettendorf (2019) and Alzuabi et al. (2021) used this model to analyze financial shocks in the system, with a primary focus on the Eurozone and the U.S., respectively. Employing the same econometric model, we shift our focus to China, investigating how Chinese financial shocks impact commodity prices. Wen et al. (2019) indicated that Chinese monetary policy affects oil prices. Here, we expand this investigation by incorporating three commodity prices: oil prices, agricultural materials prices, and metal prices.

Since Pesaran et al. (2004), several GVAR empirical studies examined various topics. Dees et al. (2007) demonstrated how U.S. shocks affect the Eurozone, capturing spillover effects. Chudik and Fratzscher (2011) investigated the dissemination of financial shocks in emerging and advanced economies. Mauro and Pesaran (2013) presented GVAR studies exploring the interconnections between economies and regions, highlighting the influence of this integration on macroeconomic variables. Eickmeier and Ng (2015) illustrated the impact of U.S. credit supply shocks on economies, while Attílio et al. (2023) argued that the monetary policy of major economies affects $CO_2$ emissions, among other relevant studies. In this context, we contribute to the existing literature by constructing a GVAR focused on China and presenting the effects of financial shocks originating in China on emerging and advanced economies.

In addition to these studies, institutions such as the International Monetary Fund (IMF) and the European Central Bank (ECB) adopt the GVAR to enhance the knowledge of policy making. One of the latest investigations is by Fareed et al. (2023), who analyzed the influence of the external environment on the inflation of the Gulf Cooperation Council (GCC). The conclusions supported the prominence of the Chinese economy in causing changes in domestic prices. In this sense, our paper advances the examination of the influence of China on economies, focusing on financial shocks.

Finally, the last contribution is to analyze the responses of Emerging Market Economies (EMEs) and Advanced Economies (ADs) to Chinese financial shocks. Typically, articles focus on analyzing only one of these groups, often EMEs, but not both simultaneously, as Chudik and Fratzscher (2011) did for the U.S. case. To address this gap, we employ the GVAR to create three regions: Asia, Latin America, and the Eurozone.

In short, China is a significant global player. The works described allow us to assert that the Chinese economy can impact domestic economies, generating spillover effects. However, to our knowledge, the literature does not adequately address the financial influence of China on the world economy. We fill this gap using the GVAR, which connects economies through bilateral trade and proxies of the world economy. Chudik and Fratzscher (2011) assisted us in understanding the 2008 financial crisis by focusing on shocks from the U.S. and portraying transmission channels in a GVAR. We construct a similar empirical exercise for China, with additions and differences described throughout the paper.

The article is structured as follows: Section 2 briefly reviews the literature; Section 3 describes the GVAR; Section 4 presents the data and econometric strategies; Section 5 displays the results; and finally, Section 6 concludes the article with a few comments.

## 2. The increasing influence of China on the international economy

Figure 1 suggests the growing influence China has on the world economy. Each line depicts the percentage of China's GDP in relation to an aggregate. China's participation in these aggregates has changed considerably since 1960. The turning point appears to be around the 1990s, when all lines show a remarkable increase.

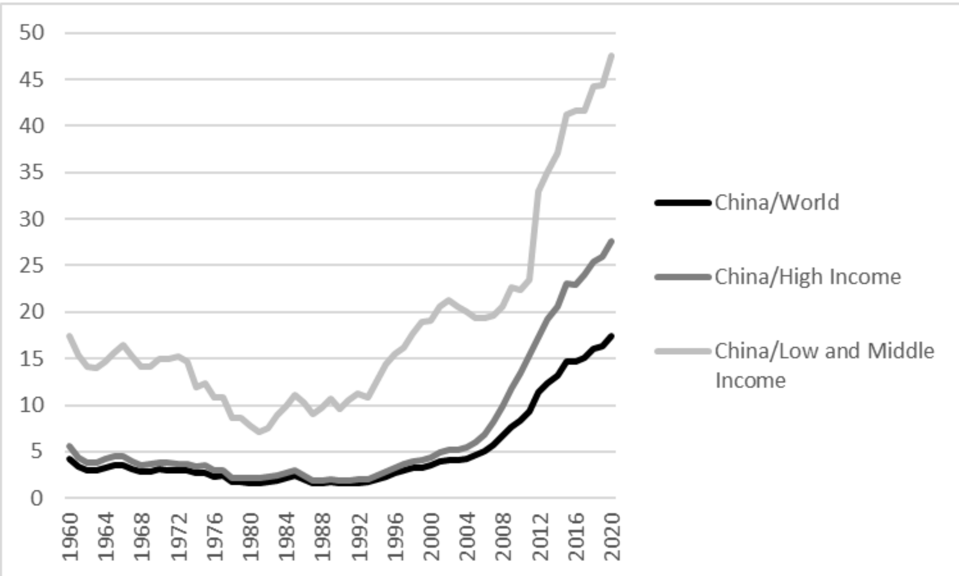


**Figure 1.** China GDP over the years (%).

In the EMEs economies (low and middle-income group), China's GDP was proportionate to 9.6% of the GDP of this group in 1990. Thirty years later, this value increased to 47.5%. This approximately fivefold increase has been investigated in the business fluctuation literature. Cesa-Bianchi et al. (2012) argued that the Chinese influence on Latin America intensified since the 1990s, with trade being the main channel of connection. In particular, the authors showed that Chinese GDP shocks had a more significant impact on Latin American economies, while the impact of U.S. shocks diminished — a difference attributed to the growing trade between China and Latin America.

Çakir and Kabundi (2017) reached similar conclusions to the Cesa-Bianchi et al. (2012) study. While the latter focused on Latin American economies, Çakir and Kabundi (2017) analyzed the Chinese influence on the BRIS group (Brazil, Russia, India, and South Africa). Their estimates reinforce the growing Chinese influence on EMEs economies, with trade serving as the connecting link between the regions.

As Cesa-Bianchi et al. (2012) asserted that the U.S. influence on Latin American economies is being substituted by the Chinese, similarly, Wall and Eyden (2016) investigated a similar change in South Africa. Their conclusion aligns with what we discussed: based on the trade between South Africa and China, they found that the Chinese influence increased over the years. Furthermore, the authors found that the U.S. influence on South Africa decreased. They used these findings to explain why South Africa remained relatively unaffected following the 2008 financial crisis. Lastly, they recommended that policymakers pay attention to the changes in foreign economies, given that the epicenter of external influence on South Africa changed from the U.S. to China.

Jenkins et al. (2008) discussed the consequences of China's pervasiveness on Latin American economies, primarily in terms of increasing trade and foreign direct investment. This study reveals both beneficial and detrimental effects of this structural change, which vary among economies and sectors. We can connect this information with Wall and Eyden (2016), whose study advanced the hypothesis that South Africa has become more sensitive to the domestic policies of China.

Chinese influence is evident not only on EMEs, but also on advanced economies. Returning to Figure 1, we observe that in 1992, China's GDP participation in high-income countries was 2%. By 2020, this value increased to 27.6%. Bloom et al. (2016) argued that the Chinese import competition has significant effects on European countries, influencing innovation and employment.

In the world economy, China's GDP increased from 1.6% in 1988 to 17.4% in 2020. Although this increase is not as remarkable as that of the low and middle-income group, it is notable how China has grown over time. According to Eickmeier and Kuhnlenz (2018), China has a significant influence on world prices.

Wang and Zhang (2021) argued that China influenced the global economic recovery from the Covid-19 pandemic. The authors reinforced their conclusion by demonstrating that China affected the economic growth of other economies. In other words, the Chinese economy generates spillover effects in the real sector. Similarly, but focusing on the financial sphere, Akhtaruzzaman et al. (2021) showed that trade integration is one of the channels through which the financial system of China influences domestic economies. We incorporate these findings into our empirical model by constructing individual models (VARX) with production and trade integration variables.

Liu et al. (2020) demonstrated that China produces lasting economic consequences on domestic economies. In particular, they also contended that China is influenced by global conditions. We incorporate this last result by allowing feedback effects of the world economy on the Chinese model. Thus, contrary to models such as VAR/VEC/SVAR, which simulate external shocks using proxies of representative variables, we construct the external shock through the Chinese model, incorporating interactions between Chinese and world variables. Additionally, i) we include financial and real channels to portray the Chinese shock, and ii) test the influence of trade integration in the results through fixed and time-varying bilateral trade, scrutinizing one of the main links between China and the world economy.

## 3. The GVAR

In this section, we describe the Global Vector Autoregressive (GVAR) model. The model constructions are primarily based on Pesaran et al. (2004), who introduced a GVAR model with one lag for both domestic and foreign variables.

The first step to build the GVAR is to create individual models with foreign and domestic variables, $VARX\ (1,1)$ (Equation 1). The term $x_{it}$ denotes the vector of domestic variables of region *i* in time *t*. Regions vary from *0* (reference region, the U.S.) to *N*, and the subscript *t* varies from *1* to *T*. The terms $a_{i0}$ and $a_{i1}$ represent the constant and the trend.

$$x_{it} = a_{i0} + a_{i1}t + \phi_i x_{i,t-1} + \Lambda_{i0} x_{it}^* + \Lambda_{i1} x_{i,t-1}^* + \varepsilon_{it}, \tag{1}$$

We use bilateral trade between regions i and j, $w_{ij}$, to construct the foreign variables, $x_{it}^*$ (Equation 2). We multiply the domestic variables of region *j* with bilateral trade, giving rise to the foreign variables. The idea behind this procedure is to simulate the international environment, i.e., how vulnerable a region is to the world economy. According to Equation 2, we display the region's exposure to international events through bilateral trade.

$$x_{it}^* = \sum_{j=0}^{N} w_{ij}\, x_{jt}, \tag{2}$$

Returning to Equation 1, we can verify that foreign variables are incorporated on the right side of the $VARX\ (1,1)$. Besides these variables, we have the idiosyncratic shock, $\varepsilon_{it}$.

Continuing the GVAR description, we create a new vector, $z_{it}$ (Equation 3), which has domestic and foreign variables.

$$z_{it} = (x_{it}\ x_{it}^*), \tag{3}$$

Now, we can rewrite Equation 1, giving us Equation 4:

$$A_i z_{it} = a_{i0} + a_{i1}t + B_i z_{i,t-1} + \varepsilon_{it}, \qquad A_i = \left(I_{k_i}, -\Lambda_{i0}\right), B_i = (\phi_i, \Lambda_{i1}), \tag{4}$$

Another useful step to solve the GVAR is to create the global vector, $x_t = (x'_{0t}, x'_{1t}, \dots, x'_{Nt})'$. This vector possesses all domestic variables of the model. We combine the global vector with the link matrix, $W_i$. The link matrix gathers the shares of bilateral trade, allowing us to write the identity (Equation 5):

$$z_{it} = W_i x_t, \tag{5}$$

Using Equation 5 in Equation 4, we have:

$$A_i W_i x_t = a_{i0} + a_{i1}t + B_i W_i x_{t-1} + \varepsilon_{it}, \tag{6}$$

We can stack Equation 6:

$$Gx_t = a_0 + a_1 t + Hx_{t-1} + \varepsilon_t,$$

$$where\ G = \begin{pmatrix} A_0W_0 \\ A_1W_1 \\ A_2W_2 \\ \dots \\ A_NW_N \end{pmatrix}, H = \begin{pmatrix} B_0W_0 \\ B_1W_1 \\ B_2W_2 \\ \dots \\ B_NW_N \end{pmatrix}, a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ a_{20} \\ \dots \\ a_{N0} \end{pmatrix}, a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ a_{21} \\ \dots \\ a_{N1} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{0t} \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{Nt} \end{pmatrix}, \tag{7}$$

Finally, we obtain the GVAR by multiplying $G$ for its inverse (Equation 8). In general, $G$ is a nonsingular matrix:

$$x_t = G^{-1}a_0 + G^{-1}a_1 t + G^{-1}Hx_{t-1} + G^{-1}\varepsilon_t, \tag{8}$$

When we have unit root in some time series, we use the GVAR in the error-correcting form (Equation 9). Pesaran et al. (2004) provide details about this procedure. One of the necessary conditions is to verify if the series are cointegrated; in other words, if they present long-term relationships.

$$\Delta x_{it} = a_{i0} + a_{i1}t - (A_i - B_i)z_{i,t-1} + \Lambda_{i0}\Delta x^*_{it} + \varepsilon_{it}, \tag{9}$$

In the next part, we present the data, aggregations, and our estimation strategy, which takes into account the Chinese evolution in international trade. The GVAR possesses valuable features, such as enabling us to assess regions' influence over time through bilateral trade. It also grants us the flexibility to model each region individually. We explore these characteristics in the following section.

## 4. Data

The database consists of six domestic variables: real GDP, real interest rate, real exchange rate, real stock exchange, consumer price index, and private credit/GDP. We obtained the first five variables from Mohaddes and Raissi (2020), where we also extracted bilateral trade. Since our aim is to investigate how Chinese financial shocks spread to the world real sector, we chose a credit definition related to the private sector. From the Bank for International Settlements (BIS), we used credit to the private non-financial sector from banks.

During the econometric exercises, we test three global variables serving as proxies for commodities prices. All of them are sourced from Mohaddes and Raissi (2020), and include oil prices, agricultural materials prices, and metal prices. Following the approach of Dees et al. (2007), we designate oil prices as a domestic variable in the U.S., while using the other variables as domestic variables in China's model. Additionally, we use two uncertainty indexes (financial and macroeconomic) related to the U.S., both obtained from Ludvigson et al. (2021). We specify when we use these variables in the results presented in the next section.

Given the importance of the U.S. economy, especially considering its capacity to influence the whole world, we must exercise caution when building its model, as is a recommended step in GVAR models (Dees et al. 2007; Attílio et al., 2023). Hence, in the primary setup for the U.S., we include only the GDP and exchange rate as foreign variables (Equation 10). The exchange rate serves as a domestic variable in all regions except the U.S., as this variable represents the domestic currency compared to the U.S. dollar. Conversely, we incorporate the exchange rate as a foreign variable only in the U.S. Another point, as previously discussed, concerns the global variables. They serve as domestic variables only in the U.S. and China, while in other regions, we treat them as foreign variables. Equation (10) helps visualize these steps:

$$
\begin{gathered}
x_{it} = (gdp_{it}, i_{it}, e_{it}, cred_{it}), \\
x_{it}^{*} = (gdp_{it}^{*}, i_{it}^{*}, cred_{it}^{*}, oil_{it}^{*}), for\ all\ regions, except\ the\ U, \\
x_{it} = (gdp_{it}, i_{it}, cred_{it}, oil_{it}), \\
x_{it}^{*} = (gdp_{it}^{*}, e_{it}^{*}), only\ for\ the\ US,
\end{gathered}
\tag{10}
$$

The terms $gdp_{it}, i_{it}, e_{it}, cred_{it}, and\ oil_{it}$ are, respectively, the GDP, interest rate, exchange rate, credit, and oil price. We do not put the domestic price ($cpi_{it}$), the stock market ($q_{it}$), and other global variables because our intention in Equation (10) is to illustrate the construction of the model. However, we change this setup during the econometric results.

Another common practice in GVAR works is to construct the Eurozone as an aggregate of countries. We followed the same procedure, forming the Eurozone by the average GDP at PPP over the years (2014–2016). Hence, eight economies (Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, and Spain) become one region. We also created two other regions comprising only emerging market economies: Asia and Latin America. We aggregated India, Indonesia, Malaysia, the Philippines, Singapore, and Thailand to constitute Asia, and we used Argentina, Brazil, Chile, Mexico, and Peru for Latin America. In addition to the advantage of categorizing economies by development level, this approach reduces the number of regions in the GVAR, which helps stabilize and estimate the model. Consequently, our model has 17 regions or 33 countries if we do not consider the aggregations.

We use two different models regarding trade integration. In the first model, we define a specific period, employing fixed weights. In practical terms, this means that bilateral trade was roughly the same over the years. However, when analyzing countries with changing trade patterns, such as China, we can use time-varying bilateral trade, where the construction of foreign variables occurs according to the bilateral trade of each period. Yet, with this option, we still have to choose the period in which to solve the GVAR. When analyzing the influence of China on the world economy, Cesa-Bianchi et al. (2012) opted for the second method.

Using alternative periods allows us to examine how the Chinese influence changes over time based on China's participation in bilateral trade. Once again, our strategy closely mirrors that of Cesa-Bianchi et al. (2012). We used weights relative to 1985, 1995, 2005, and 2014–2016. Additionally, we also adopted these periods with their averages: 1985–1987, 1995–1997, 2005–2007, and 2014–2016, which helps smooth possible changes in the trade pattern. Finally, due to data limitations, we employed the period 1985Q4–2016Q4, with all variables in logarithmic form.

In the appendices, Table A.1 presents the descriptive statistics of the variables. Tables A.2 and Tables A.3 show the unit root test (weighted symmetric). The results indicate that the time series are nonstationary in levels but stationary in first differences. Table A.4 displays the lags of the VARXs (using the Akaike information criterion) and the number of cointegrating relationships. Therefore, based on the information in Tables A.2–A.4, we adopt the GVAR in the error correction form (Equation 9).

Table A.5 examines the stability of the cointegrating vectors (CV). The persistence profile simulates a generalized shock in the cointegrating vectors and show the periods they take to return to equilibrium. Most vectors return close to zero by period eight, indicating stability of the vectors.

## 5. Econometric results

### *5.1. Credit shock*

This section presents the econometric results of the model. We explore the Chinese negative credit shock and analyze the responses of emerging economies and relevant world regions.

The next five figures depict a negative credit shock on China and the responses of regions' variables, with all values in percentages. The dashed lines represent bootstrap confidence intervals at 90%. In this initial setup, the model includes GDP, exchange rate, private credit, interest rate, and the agricultural raw materials index — our proxy for commodities prices. Throughout the article, we use various proxies to illustrate the volatility of commodities resulting from Chinese shocks. We use the average of bilateral trade for the years 2014–2016.

Figure 2 shows that the Chinese credit market has a significant influence on the world economy. Starting with the emerging market economies, both regions' GDP falls right after the credit shock. Asia exhibits an accumulated fall of GDP over 0.2%, while Latin America displays a reduction of 0.6%, but Asia's estimates are statistically nonsignificant. These results align with those presented by Cesa-Bianchi et al. (2012), Bloom et al. (2016), and Çakir and Kabundi (2017), with the distinguishing characteristic that the Chinese influence occurred initially in the financial sector.

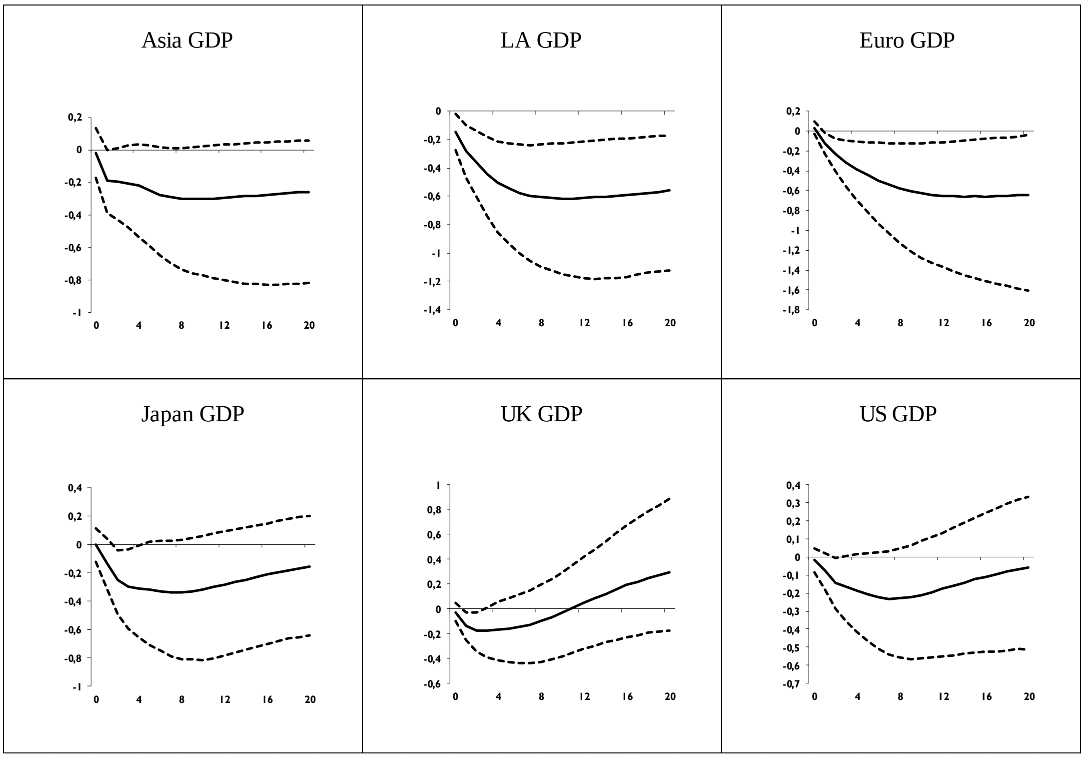


**Figure 2.** GIRF of China negative credit shock and GDP responses.

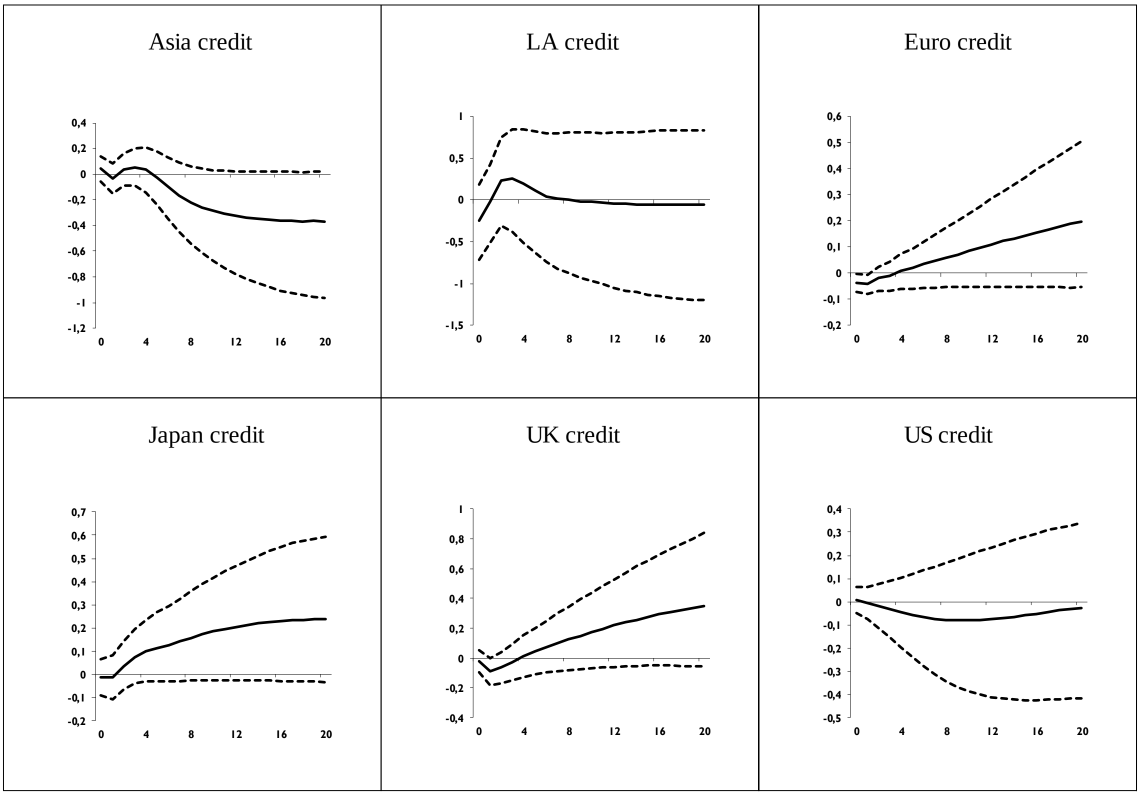


**Figure 3.** GIRF of China negative credit shock and credit responses.

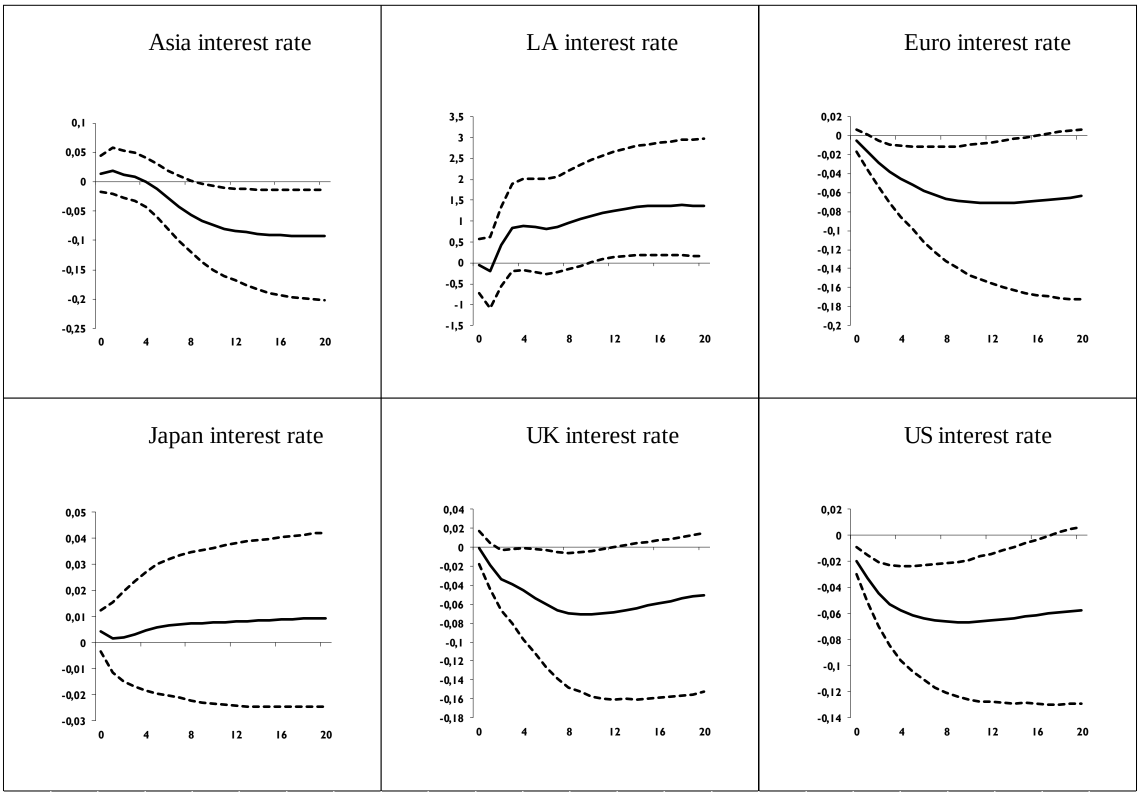


**Figure 4.** GIRF of China negative credit shock and interest rate responses.

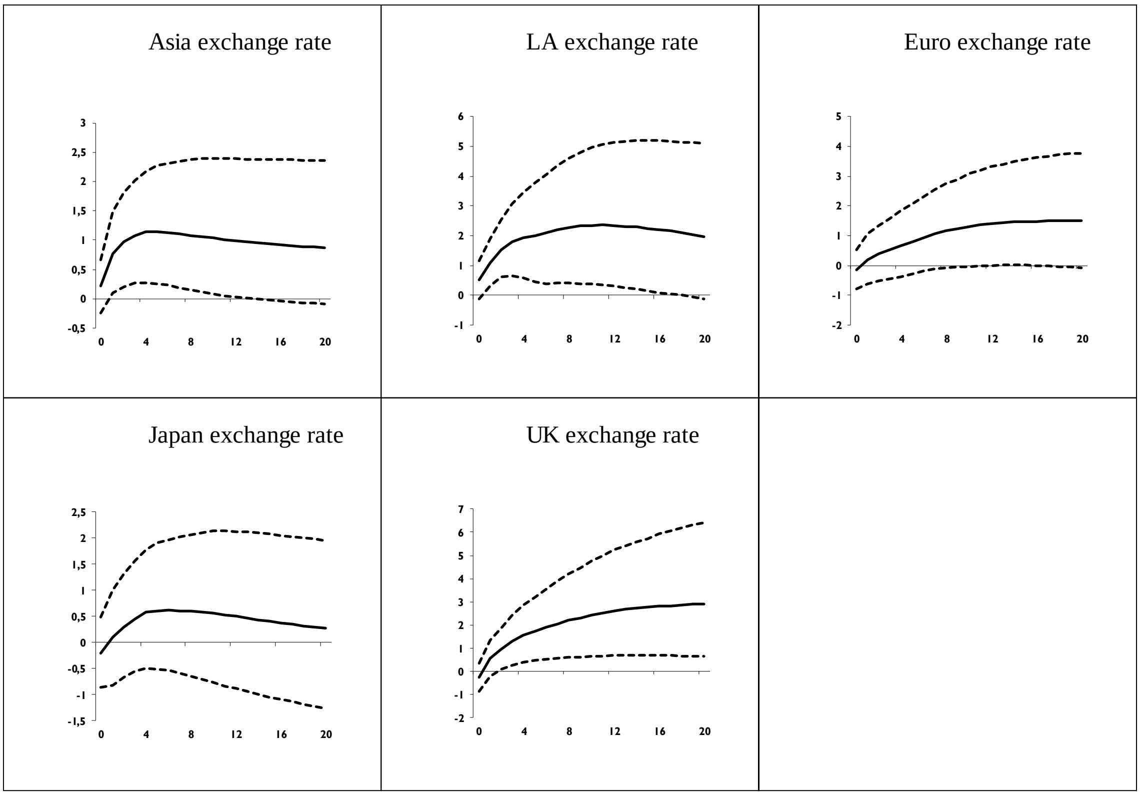


**Figure 5.** GIRF of China negative credit shock and exchange rate responses.

Production also decreased in the advanced regions. Eurozone GDP had a trajectory similar to that of Latin America, with a fall of 0.6%. In the other three regions, Japan, the U.K., and the U.S., the GDP responses were statistically significant only in the first quarters. The negative credit shock seemed to affect these economies in the short term. Comparing results between EMEs and advanced economies, the estimates suggest that a credit shock from China is more prominent in the former regions, except for the Eurozone.

According to the model setup, we have three possible transmission channels to explain how a financial shock affects the real sector (GDP): credit, interest rate, and exchange rate. In Figure 3, which displays the credit market, we see that the estimates do not support that credit connects the financial and real sectors. The Eurozone and the U.K. experienced credit falls in the first period, but they became statistically nonsignificant in both regions after that. Therefore, we must explore transmission channels in other segments of their economies.

Searching for a possible transmission channel, Figure 4 reports interest rate responses. Contrary to Figure 3, all regions had statistically significant estimates, with Japan being the only exception. Asia, the Eurozone, the U.K., and the U.S. exhibited expansionary monetary policies, but the value of the interest rate change is negligible. Asia had the highest percentage change with a fall of 0.1%. Although interest rates reacted to the Chinese shock, the movements were very low in values. The exception is Latin America, where we observe the interest rate increase by 1% at the end of the period. As illustrated in the next figure, the response in Latin America can be explained by noting that the region suffers one of the strongest capital outflows after the shock.

Figure 5 presents the exchange rate, our last possible transmission channel. The results suggest that the Chinese credit shock spread to the other regions in this economic segment in particular. Asia, Latin America, the Eurozone, and the U.K. had increases of 1%, 2%, 1.5%, and 3%, respectively. We observe the famous process of "flight to quality", in which capital flows to safer places, specifically the U.S. Our estimates show that the Chinese shock triggers the depreciation of domestic currencies. We conclude that a negative credit shock from China can cause profound volatility in international financial markets, with effects reaching domestic real sectors of economies on different continents. However, Japan's estimates were once again statistically nonsignificant.

With this information, we can now build a coherent picture. The Chinese negative credit shock affects both emerging and advanced economies through the exchange rate channel, triggering capital outflows. In most regions, the central banks react by reducing interest rates, while in Latin America, they tighten monetary policy by increasing interest rates. One possible explanation is the considerable outflow of capital observed in the region; however, this hypothesis fails to justify the case of the U.K., which experienced a 3% increase in its currency (depreciation) and implemented an expansionary monetary policy.

Apart from the exchange rate, in Asia, credit also served as a transmission channel for the shock. The final result is the negative influence of the Chinese shock on production and generalized declines in GDP. Therefore, shocks in the Chinese financial market have the potential to provoke an international recession.

The Chinese shock affected other regions through another channel as well: commodity prices. Figure 6 shows that the negative credit shock provoked a negative effect on the commodity prices. In the first year of the shock, the price fell by around 4%, ending the series at 5%. In general, emerging economies are dependent on primary exports, particularly commodities. Thus, the fall in Figure 6 suggests an additional channel through which the Chinese shock can impact economies.

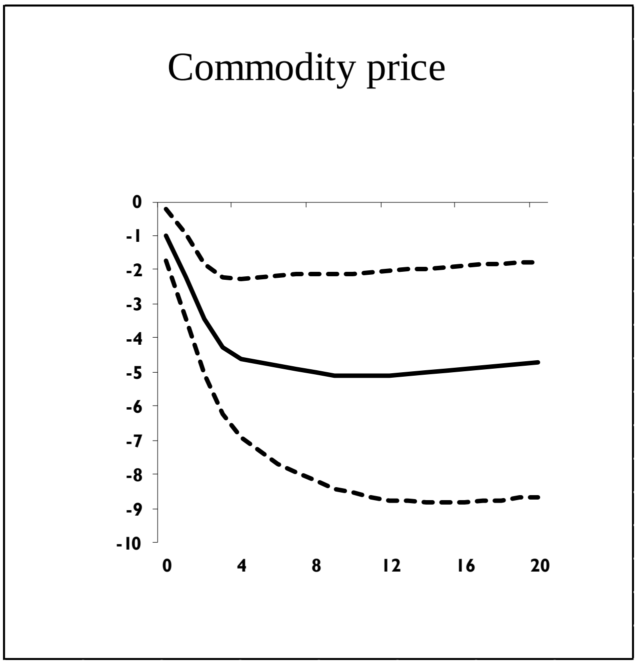


**Figure 6.** GIRF of China negative credit shock and commodity price response.

Although the GVAR does not provide shock identification, when we focus on analyzing the transmission of shocks, we can extrapolate the results and reach the conclusion that the credit shock triggers capital outflows. This flight to quality, in turn, impacts domestic production. Additionally, we can assert that the fall in commodity prices reinforces the negative effect from the Chinese credit market. Furthermore, the credit shock exemplifies a known characteristic of China portrayed in works like Eickmeier and Kuhnlenz (2017): the significant influence of this country on world inflation, a role confirmed by the estimates in Figure 6.

While Eickmeier and Kuhnlenz (2017) analyzed the impact of real shocks from China on world inflation, here we applied a financial shock, which had an influence on commodity prices.

*5.2. Exchange rate shock*

In this subsection, we made a few changes to the model setup used in the past subsection. The first change involves replacing the commodity price with the stock market variable as a domestic variable. The second change pertains to our treatment of the trade integration; specifically, we employ time-varying bilateral trade to construct the foreign variables.

To solve the model, we use data from four periods: 1985, 1995, 2005, and 2014–2016. Finally, we examine the impact of a negative exchange rate shock in China. Given that the exchange rate is based on the domestic currency to the U.S. dollar, this shock reflects the appreciation of the Chinese currency. Figures 7, 8, 9, 10, and 11 display the results.

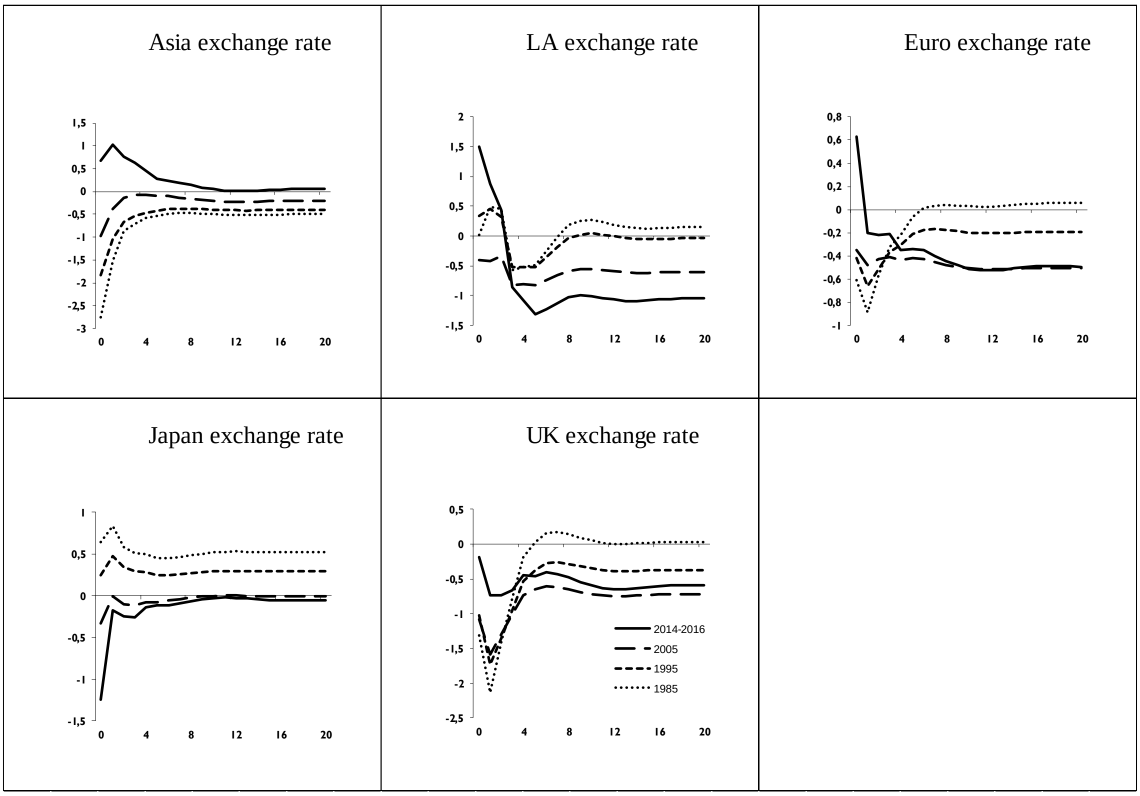


**Figure 7.** GIRF of China negative exchange rate shock and exchange rate responses.

Figure 7 indicates that the Chinese influence increased in Latin America, the Eurozone, and the U.K. over time. This trend is particularly evident in Latin America, where the exchange rate experienced a 1% increase in 2014–2016, reflecting an appreciation of the domestic currency. Conversely, in Asia and Japan, the impact of the exchange rate shock diminished over time.

Chinese spillover is evident in Figure 8, where the credit response becomes increasingly pronounced over time in Latin America, the Eurozone, and Japan. In Latin countries, the credit exhibited an accumulated expansion of around 0.5%. While shocks dated in 1985 adversely affected the U.K., this pattern shifted with shocks in the new millennium, resulting in positive credit responses. In contrast, the U.S. exhibited an inverse behavior: shocks in 1985 were favorable but became detrimental to its economy.

The Chinese shock did not induce changes in domestic monetary policies, as depicted in Figure 11—a conclusion consistent with that of Subsection 5.1. Latin America stood out as the only region where the impact of China was noteworthy, given that the interest rate increased by 1%. In contrast, the remaining economies exhibited values too small to be considered relevant.

Figure 10 suggests that the stock market is the primary transmission channel of this shock. Domestic markets in all regions responded positively to the exchange rate shock, ranging from 1% to 2%, highlighting the sensitivity of this segment to international shocks. Moreover, the stock market response increased in line with China's presence in the world economy, as evident from the lines depicting the weight of bilateral trade.

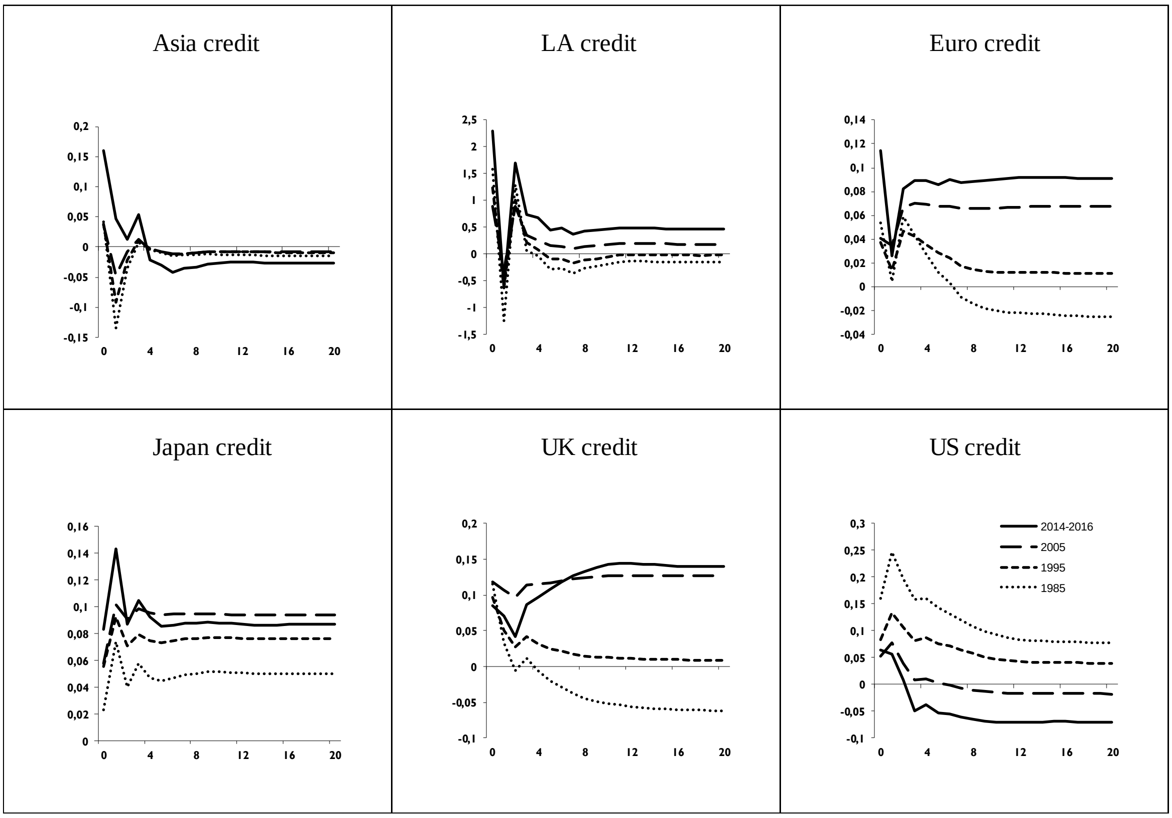


**Figure 8.** GIRF of China negative exchange rate shock and credit responses.

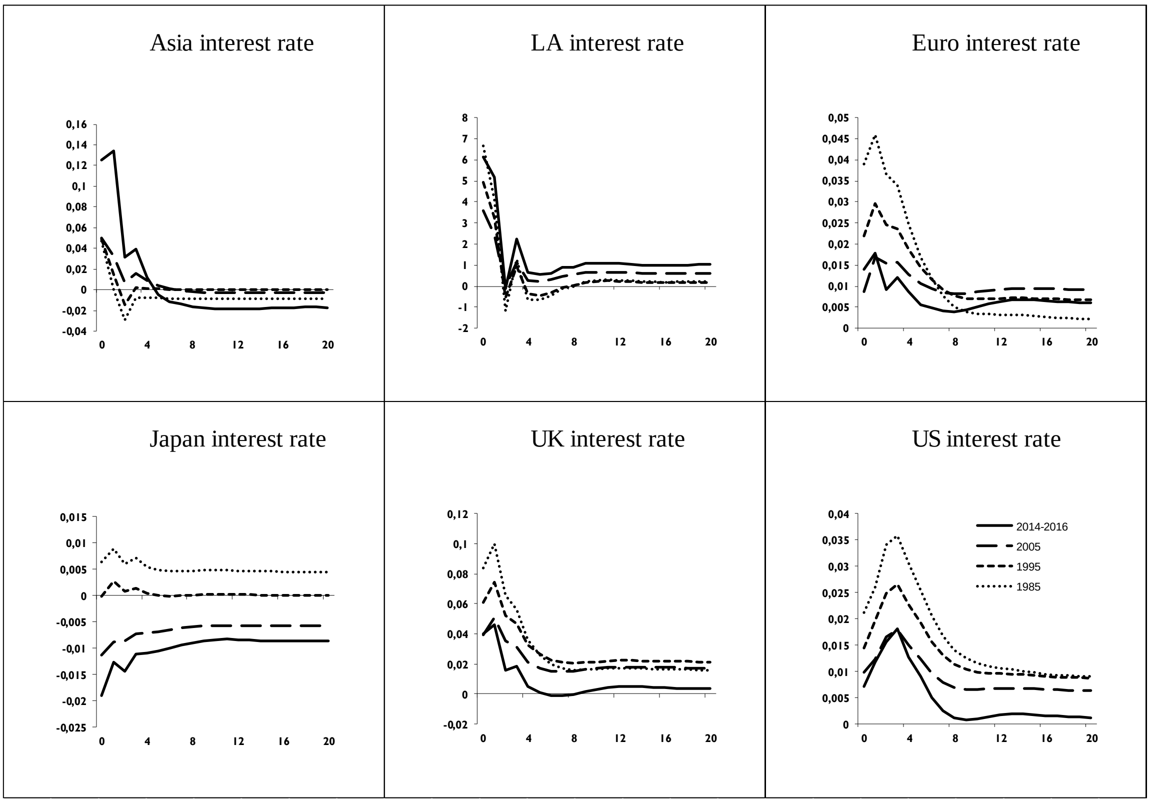


**Figure 9.** GIRF of China negative exchange rate shock and interest rate responses.

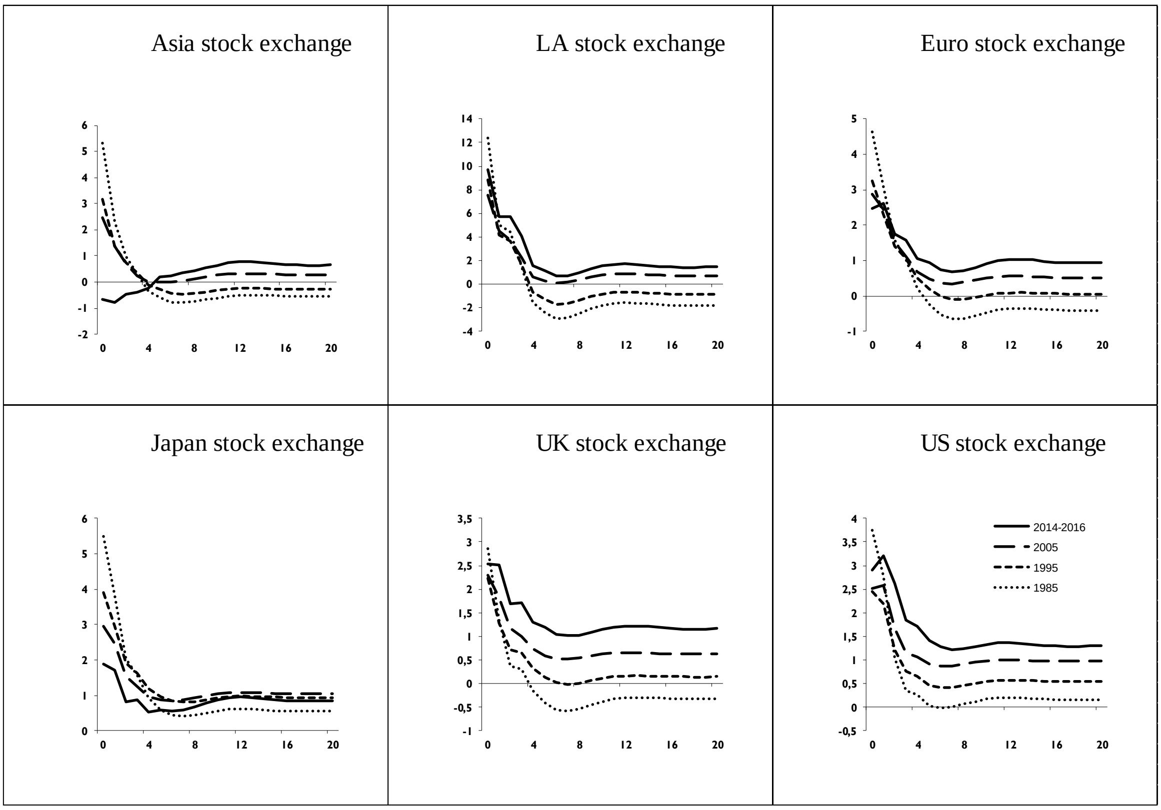


**Figure 10.** GIRF of China negative exchange rate shock and stock exchange responses.

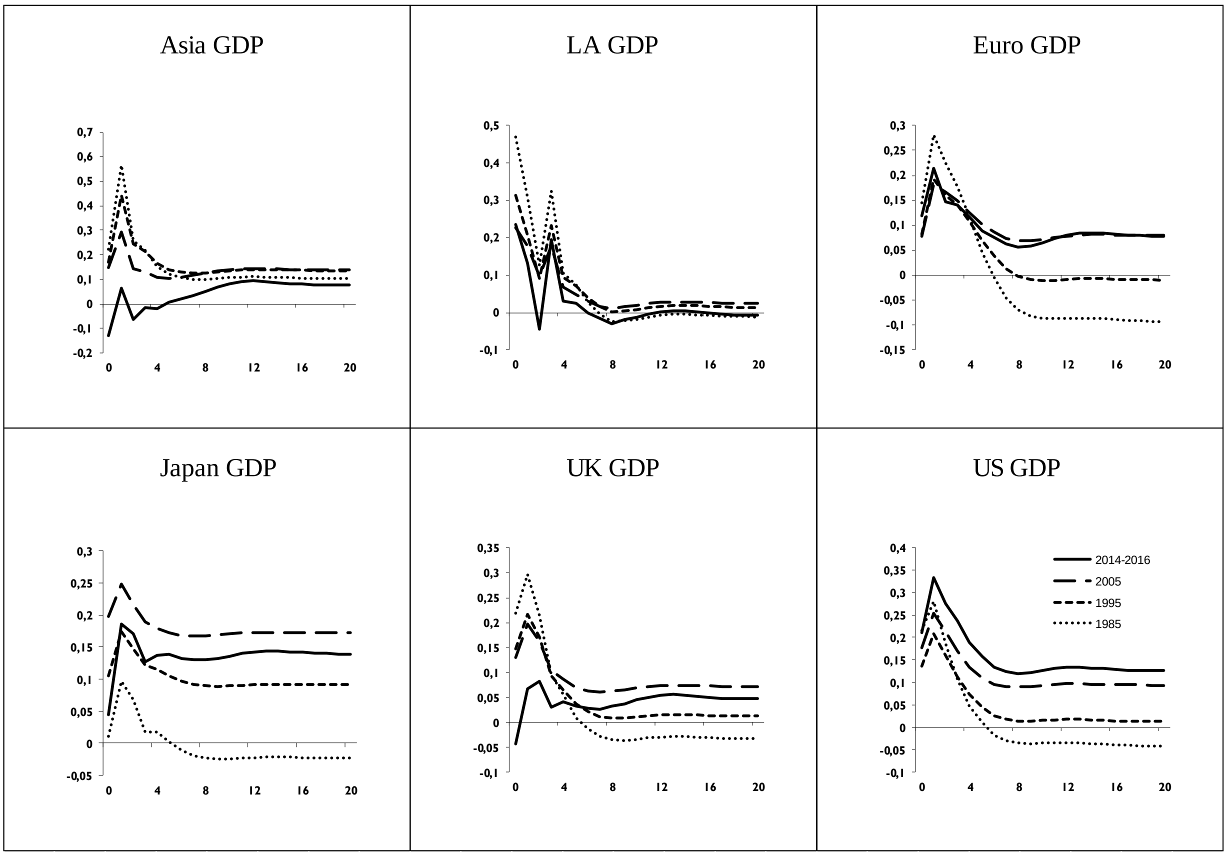


**Figure 11.** GIRF of China negative exchange rate shock and GDP responses.

The final figure in this subsection, Figure 11, reinforces the conclusion that China's financial system can trigger international volatility in the real sector, and this shock has become more prominent in the new millennium. This trend is evident in all advanced economies, while emerging economies did not exhibit this feature. The GDP of Latin America and Asia did not display a discernible pattern of changing behavior over the decades.

As the Chinese negative exchange rate shock led to booms in the industrialized regions, our initial candidate for the transmission channel was the stock market, which increased in value following the shock. Additionally, in the Eurozone, Japan, and the U.K., the private credit segment also reinforced the positive effect of the exchange rate shock on domestic production. In Latin America, the shock triggered the expansion of private credit and the stock market, but these impacts may have been nullified by the appreciation of the domestic currency, leading to negative effects on the export sector. The results in Asia were inconclusive because the estimates for this region did not allow us to formulate a reasoning about the shock transmission.

When we compare the exchange rate shock with the credit shock, we realize that these shocks spread via different channels. The stock market stood out in the first case, while the exchange rate played a role in the latter shock. As a common ground, both financial shocks affected the world economy, causing significant macroeconomic volatility and impacting the domestic production of emerging and advanced economies.

*5.3. U.S. Uncertainty and commodity prices*

We test the Chinese financial influence using two uncertainty measures: financial uncertainty, an index comprising a multitude of financial series, and macroeconomic uncertainty. We obtained both indexes from Ludvigson et al. (2021). As most of the series encompassing these indexes are related to the U.S. and considering the U.S.'s role in the world economy we treat these variables as global variables, including them as domestic variables only in the U.S. model.

We also test the impact of China on other commodity prices using the base metals price index and the oil price, both extracted from Mohaddes and Raissi (2020). We treated both as global variables in the GVAR. We included the first variable as a domestic variable in the Chinese model, while in the U.S. model, we followed Dees et al. (2007) and used the oil price.

Figure 12 depicts the same shock investigated in Section 5.1, a Chinese negative credit shock. Financial uncertainty was statistically nonsignificant in all periods. On the other hand, macroeconomic uncertainty became statistically significant from the fifth period onwards.

To better understand these results, we can examine the U.S. responses to the shock. Due to space constraints, we do not display GIRFs of other regions, but they suggest the following about the uncertainty fall: the domestic currencies depreciated in most regions after the shock, indicating an appreciation of the U.S. dollar, which could have contributed to reducing uncertainty in this economy.

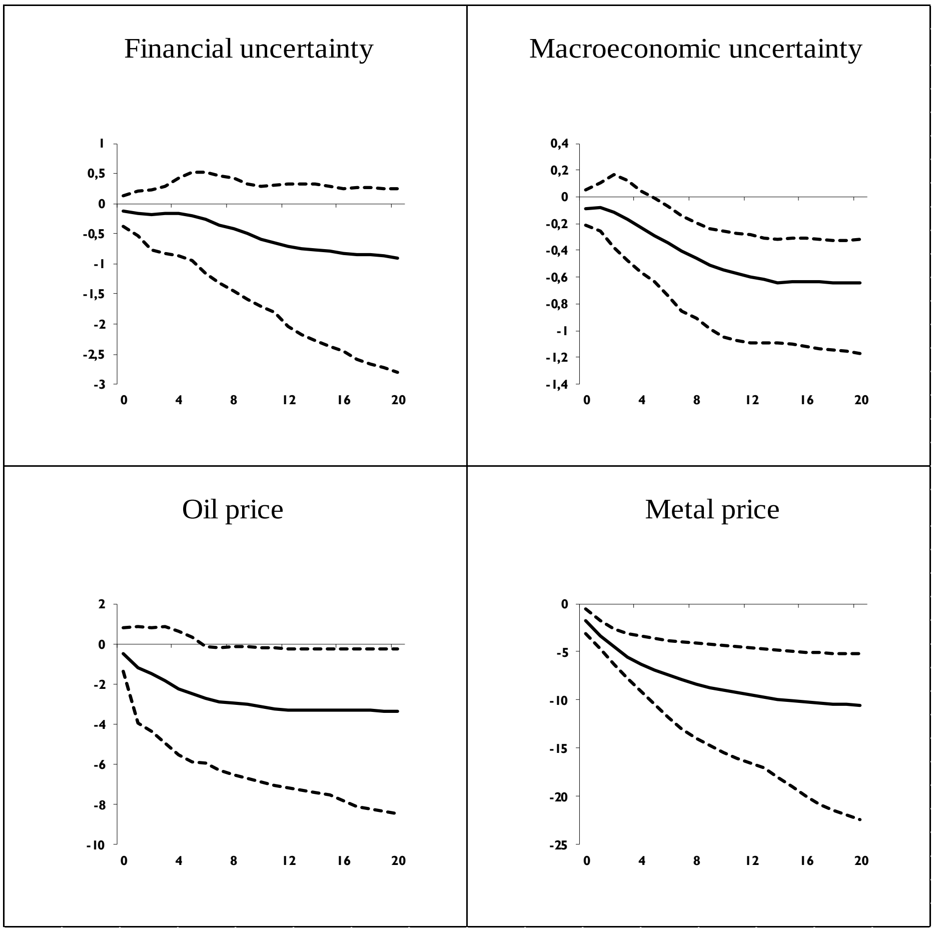


**Figure 12.** GIRF of China negative credit shock and uncertainty and commodities responses.

While the uncertainty results may not have been as conclusive as we hoped, we can draw conclusions when analyzing commodity price results. Both indexes experienced considerable declines: around 3% in oil and an impressive 10% in metals. These estimates confirm the significant role that China plays in the commodities market, demonstrating that China can affect world inflation through financial markets.

### *5.4. Variance decomposition*

We adopt the Generalized Forecast Error Variance Decomposition (GFEVD) to measure the influence of China on domestic variables. Table 1 illustrates how financial shocks influence specific variables. In Model 1, we present the model from Section 5.1, examining how the credit shock affects domestic credit aggregates. Similarly, in Model 2, we employ the model from Section 5.2 to assess how the exchange rate shock from China impact domestic exchange rates.

We created two groups: the first comprising emerging economies (Asia and Latin America), labeled EME, and the second consisting of advanced economies (the Eurozone, Japan, the U.K., and the U.S.), labeled AD. We conducted the analysis separately to observe how Chinese shocks affect domestic variables over the periods 1985 and 2014–2016.

**Table 1.** GFEVD of China.

| Groups | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Credit | | | Exchange rate variance | | |
| | 0 | 4 | 20 | 0 | 4 | 20 |
| EME (1985) | 0.058 | 0.081 | 0.033 | 0.150 | 0.133 | 0.035 |
| EME (2014–2016) | 0.238 | 0.179 | 0.067 | 0.173 | 0.087 | 0.026 |
| AD (1985) | 0.169 | 0.096 | 0.050 | 0.008 | 0.008 | 0.003 |
| AD (2014–2016) | 0.034 | 0.026 | 0.056 | 0.031 | 0.018 | 0.009 |

Beginning with the emerging economies (EMEs), the Chinese credit shock increased its explanatory power in the 2014–2016 period, more than doubling its influence. The same is not true for the advanced economies, in which the Chinese credit has lost ground, although in the last period (2014–2016), it surpassed the influence of the base year of comparison (1985). China has a growing influence on advanced economies (ADs) when we look at the exchange rate. Although the values are lower than those of EMEs, we still detect the Chinese influence on the domestic exchange rates of advanced economies. The explanatory power tripled in the last period.

### *5.5. Robustness test*

When investigating Chinese shocks, Cesa-Bianchi et al. (2012) used time-varying bilateral trade. Varying the weights changes how we construct foreign variables. By implementing time-varying weights, the process to calculate these variables considers bilateral trade over the periods.

In Subsection 5.2, we incorporated this strategy to analyze another Chinese financial shock. Here, we closely follow Cesa-Bianchi et al. (2012), but we make some important changes. We also assess the Chinese shock in the periods 1985, 1995, and 2005. However, due to a larger period, we extend the investigation to 2016. Furthermore, we consider the averages of these periods instead of focusing only on the specific years. Hence, we evaluate how the Chinese shock behaved in 1985–1987, 1995–1997, 2005–2007, and 2014–2016. We believe this approach smooths changes in bilateral trade over time. Finally, while Cesa-Bianchi et al. (2012) employed time-varying bilateral trade, we opt for fixed weights. Again, we made our decision considering that using alternative setups demonstrates the robustness of results.

The objective of this exercise is to observe if China's influence increased over time, correlatively with its growing participation in world GDP and international trade. Figure 13 presents estimates of the GDP for the four periods. We hypothesize that Chinese financial influence enhanced *pari passu* with its integration into the world economy. As we have four lines in each graphic of Figure 13, we do not display bootstrap intervals.

The first part of Figure 13 confirms what we discussed: the financial influence of China on the world economy has increased over time. This finding is clearer in the cases of Latin America and the Eurozone, while in Asia, the shock impact of 2005–2007 is similar to 2014–2016. In Japan, the U.K., and the U.S., we can also see the growing influence of China, although it is not as apparent as the results portrayed in the upper part of Figure 13. We should keep in mind that, as displayed in Figure 2, the estimates for these regions are statistically significant only in the initial quarters.

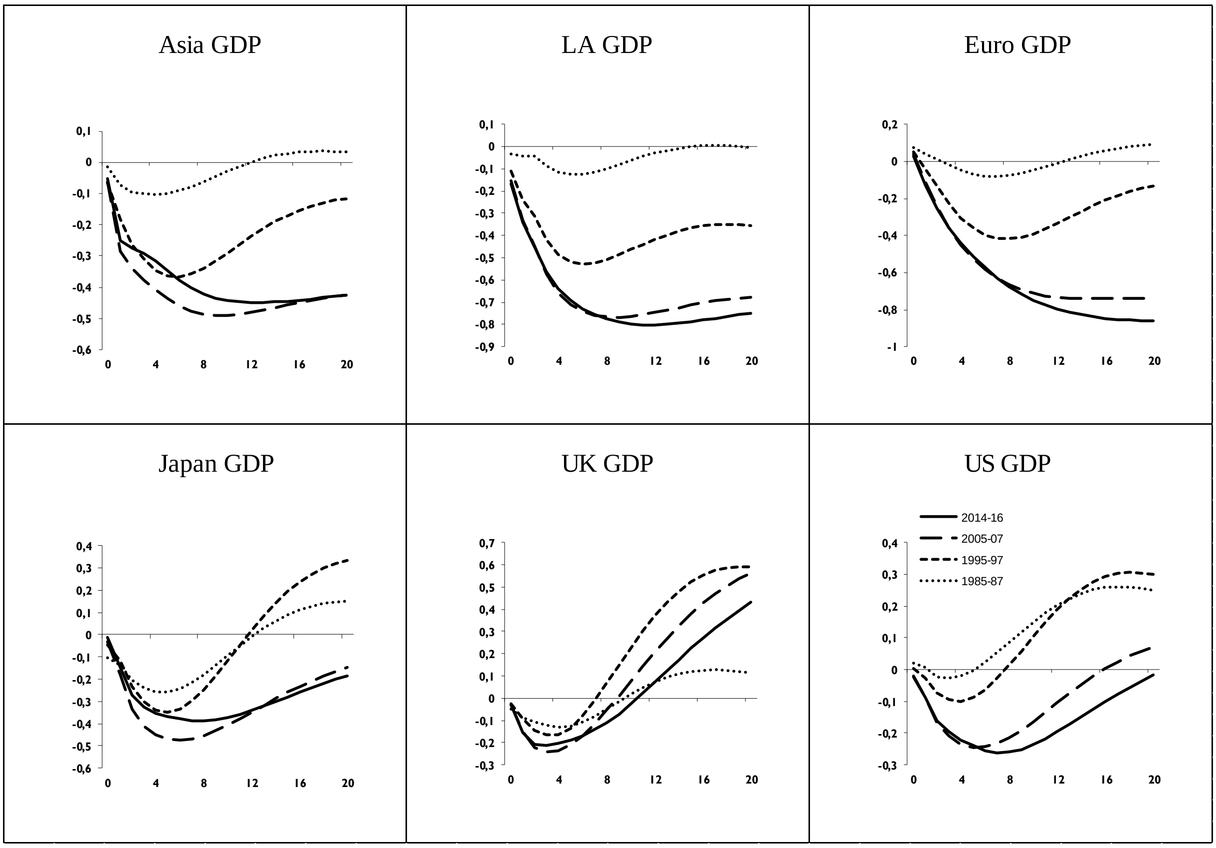


**Figure 13.** GIRF of China negative credit shock and GDP responses with alternative weights.

Figure 14 reinforces the previous conclusions. The negative credit shock depressed commodity prices. The impact of the shock gained traction over the decades, with a division between the old and new millennium. Comparing Figures 13 and 14, we can assert that although the Chinese financial influence increased in more recent periods, this gap has stopped showing relevant differences if we look at the periods 2005–2007 and 2014–2016.

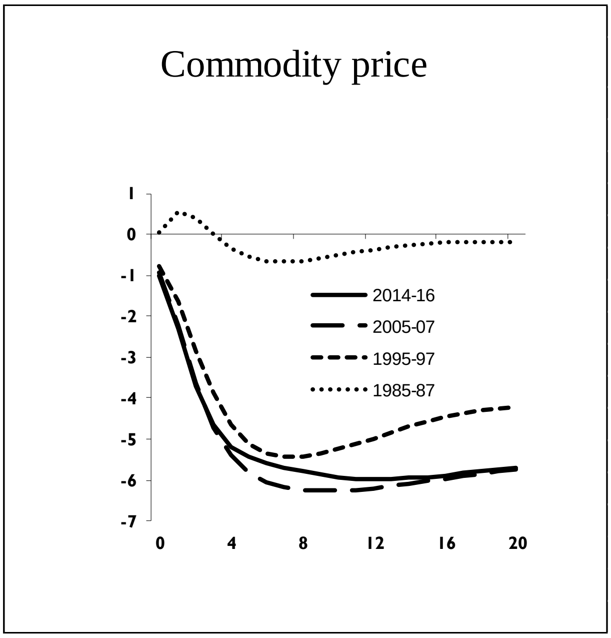


**Figure 14.** GIRF of China negative credit shock and commodity price responses with alternative weights

The Chinese financial influence increased over the decades. Cesa-Bianchi et al. (2012) stated that China augmented its influence in the real sector, mainly regarding GDP shocks. We argue that this is also true in the financial markets.

Finally, concerning the configuration of trade integration between economies, our econometric exercises support the conclusion that the results remain consistent regardless of fixed or time-varying bilateral trade.

## 5. Conclusions

This article explored the Chinese financial influence on emerging and advanced economies. The estimates suggest that private credit and exchange rate shocks from China can provoke fluctuations in the international economy, affecting domestic financial markets and production.

Concerning future research, we recognize that future researchers may be able to find an alternative proxy than bilateral trade as a variable connecting China to the other regions. We consider this an area in which future studies could focus and improve. Moreover, we hope other authors analyze the points investigated here and compare estimates to test our conclusions.

As Chinese financial shocks can trigger macroeconomic fluctuations, policymakers should remain vigilant about developments in China. Specifically, potential policy measures include: i) allowing the exchange rate to fluctuate to mitigate external shocks, ii) using public funds to alleviate the adverse effects on the population (thus, governments should run primary surpluses to increase available funds and decrease the level of public debt), and iii) central banks accumulating international reserves to address critical situations. Naturally, empirical studies and practical experience can assist in guiding these policies. Our contribution is to demonstrate that the financial system of China has the potential to destabilize domestic economies.

**Use of AI tools declaration**

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

**Conflict of interest**

All author declares no conflicts of interest in this paper.

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