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Research article

How trade drives fluctuations in macroeconomics in China – A multi-level dynamic factor approach☆

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ABSTRACT

Investigating how international trade with different regions and in different indus- tries affects the macroeconomy is crucial for policymaking and economic forecasting, particularly in the context of trade frictions. Using a dynamic hierarchical factor model (DHFM) and factor-augmented vector autoregression (FAVAR) model, we extract factors from extensive trade data to explore their impacts on and interactions with the macroeconomy.

Our findings reveal three key aspects. First, a positive shock to the overall trade factor generates positive macroeconomic effects, though with notable regional varia- tions. The OECD factor triggers inflationary pressures and monetary tightening in both China and the US, whereas the ASEAN factor leads to policy divergence—China opts for monetary easing against US tightening—accompanied by improved foreign direct investment (FDI) inflows and stock market performance. Second, in the in- dustry dimension, positive shocks to the medium-tech and high-tech manufacturing sector demonstrate sustained industrial growth and positive FDI trends, despite some financial market uncertainties. Third, regarding policy interactions, we find a contrac- tionary US monetary policy shock significantly impacts China's trade and macroeconomic cycles,whereas a contractionary Chinese monetary policy shock shows relatively ambiguous effects.

1. Introduction

China's economic transformation over the past four decades has been fundamentally shaped by its reform and opening-up policy. Foreign trade, as one of the three pillars of economic growth, has been instrumental not only in driving rapid economic development but also in facilitating industrial advancement and upgrading. However, the current global trade landscape presents unprecedented challenges that warrant careful examination of trade risks and their transmission mechanisms.

China's current trade landscape is facing multiple interconnected challenges. According to statistics, global commodity trade volume fell by 1.2 % in 2023, marking the third global trade contraction since the establishment of the World Trade Organization (WTO) in 1995, following the 2009 global financial crisis and the outbreak of the COVID-19 pandemic in 2020. Import demand,

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especially in regions such as Europe, has sharply declined, posing even greater difficulties for trade.

The dire situation facing trade involves multiple factors: the escalation of geopolitical conflicts such as Russia-Ukraine and Israel-Palestine; the US entering a tightening cycle, leading to widespread adoption of contractionary monetary policies in developing economies, exerting immense pressure; most importantly, the US is currently spearheading a trend towards deglobalization, aiming to comprehensively suppress China. These factors have had a significant negative impact on the global trade chain, including reduced global demand, decreased supply-chain stability, rising raw-material costs, and even the risk of overall supply-chain decoupling. According to the latest "Global Trade Outlook and Statistics" report, economists at the WTO point out that although inflation pressures have eased in 2024, regional conflicts, geopolitical tensions, and economic policy uncertainty still pose significant downside risks. The negative impact of trade will have a huge influence on the Chinese economy.

In the current era confronted with unprecedented changes, China faces the daunting task of promoting stable economic growth and upgrading its industrial structure. The recent Political Bureau meeting of the CPC Central Committee on December 9, 2024, which for the first time emphasized "strengthening extraordinary counter-cyclical adjustments," signals a more proactive approach to addressing these challenges, particularly in trade and economic domains. Against this backdrop, smoothing out trade risks and delineating the structural characteristics of trade risks becomes particularly important. This effort involves dissecting and understanding trade uncertainties, such as dividing trade uncertainties by country or region, or by different types of commodities. This paper aims to explore these issues to help us unravel the most critical trade elements and take targeted measures.

In addition to factors from the real economy, the impact of monetary policy is equally important and needs to be included as a controlled variable in the analytical framework, exploring its mechanism of joint impact with trade variables on macroeconomic outcomes. This paper also attempts to incorporate this factor into the research framework.

In this paper, we use the dynamic hierarchical factor model (DHFM) to structurally decompose the trade data according to regions and industries, extract regional and industrial factors, and document the impacts of these factors on trade. And then we feed the factor extracted from the DHFM and macro data into the factor-augmented vector autoregression (FAVAR) model to explore the interaction between trade, the macroeconomy, and monetary policies.

The application of the dynamic factor model (DFM) has three advantages. The first is dimensionality reduction: the DFM effectively reduces the dimensionality of data by utilizing common factors. This reduction simplifies data analysis and interpretation while improving model efficiency. The second is utilization of data structure: the DFM better utilizes the structure of data than traditional factor models. It considers changes in factors across different levels and allows for time-varying intercepts in factor transformation equations. This flexibility enables the model to better adapt to the characteristics of actual data. The final advantage is block structure: the block structure in DFM provides an effective way to handle covariates from different sources. It can take into account changes that are not sufficient to be considered common factors, thereby avoiding misinterpreting these changes as weak common factors or individual errors.

The application of the FAVAR method has the following four advantages. First and foremost, we are able to avoid concerns about degrees of freedom by using a large amount of data for analysis in the conventional VAR model. For example, our FAVAR model includes over 130 macroeconomic indicators in China to fully utilize available information. Second, it helps address potential endogeneity issues arising from the fact that trade behavior in different countries may be influenced by the overall macroeconomic conditions of those countries. Third, this method reduces reliance on arbitrary choices of which variables to include in VAR. We can directly provide many indicators and extract factors from them. Fourth, the FAVAR method allows us to study the overall impact of trade variables on the macroeconomy.

Our main findings using the DHFM and FAVAR model are, first, positive shocks on overall trade factors have positive effects on the macroeconomy. Second, when we arrange the trade data by regions, we find positive shocks on trade with different regions such as OECD, ASEAN, and Belt and Road economies all affect the Chinese economy positively but to different degrees. Third, when we group the trade data by industries, positive shocks on low-tech industries have only short-term stimulus effects on the economy, whereas positive shocks on medium- and high-tech industries can generate long-lasting effects. Fourth, in terms of monetary policy, US monetary policy is driving China's trade cycle, whereas China's monetary policy overall remains relatively passive, because we can see a positive shock to China's monetary policy basically does not have significant impacts on trade and other macro variables.

1.1. Related literature

The literature relevant to this paper covers five main aspects.

First is the exploration of the relationship between trade and macroeconomics. This strand of literature can be traced back to David Ricardo's theory of comparative advantage, and the classical H-O theory systematically describes how countries should engage in trade based on their endowments to promote welfare enhancement. Baldwin (1992) suggests trade not only has static comparative advantage effects but also promotes dynamic effects on capital accumulation, thereby driving economic growth. The literature also discusses the so-called "comparative advantage trap." For instance, Mazumdar (1996) argues that whether trade promotes growth depends on the structure and direction of trade. If trade does not bring about capital accumulation, it will not lead to economic growth either. Levin and Raut (1997) find primary products have a small effect on economic growth, whereas exports of industrial goods have a stronger impact. Chu et al. (2023) explore the impact of exports on the economy by establishing an open-economy Harrod growth model and higher export demand does not significantly affect long-term economic growth but can increase employment levels during the transition period, leading to a larger market size and earlier economic takeoff, as well as higher growth rates during the transition period. Some literature also studies China-related issues. For example, using export data from multiple countries to examine the relationship between the upgrading of export technology structure and economic growth, Hong and Liu (2013) find the relative

productivity advantage of China's export sectors has no significant effect on economic growth, but the production of export technology structure does. Liu and An (2011), decomposing the sources of growth in the Chinese economy from 1987 to 2011, find the positive effect of external demand on the economy varies at different stages and has different effects on different industries. Studying the sharp decline in China's exports after the 2008 financial crisis, Fan et al. (2023) find the increase in external market uncertainty reduces the expected value of enterprise export and borrowing capacity, leading to a reduction in exporters and a smaller average export scale, resulting in negative impacts of exports both in depth and breadth.

The second strand of literature is measuring trade-risk methods. Most of the literature attempts to construct indicators based on specific trade-related data. For example, some studies focus on trade policy risks, such as Benguria et al. (2022), who establish the trade policy uncertainty (TPU) index through text analysis of annual reports of listed companies in an attempt to measure the changes in TPU risks faced by Chinese companies under the background of the China-US trade war and establish connections with corporate investment, R&D expenditure, and profits. Heise et al. (2017) find reducing TPU can increase the precise, high-quality purchasing relationships between enterprises and suppliers, thereby benefiting both upstream and downstream enterprises. However, overall, the literature lacks systematic and structural measurement and evaluation of trade risks as a whole.

The third strand is on the DFM or DHFM. Similar to the FAVAR model, the DFM primarily serves for data-dimensionality reduction, extracting core factors from multidimensional data. Sargent et al. (1977) and Geweke (1977) first proposed the DFM in the field of economics, and subsequent expansions and applications in the field of economics have occurred. Forni and Gambetti (2010) construct a DFM using 112 macroeconomic variables in the US to identify monetary policy shocks, whereas Barigozzi et al. (2014) use a similar method to study the situation in the euro area. Liang and Gao (2007) also use the DFM to decompose the volatility factors of housing prices in 26 cities in China. They show the DFM model can effectively serve for dimensionality reduction and structured decomposition of datasets.

Fourth is the literature on the FAVAR method. The classical problem with the VAR method is that too many variables can lead to over-parameterization of the model, whereas simplifying variables may omit key information. The FAVAR method aims to address this problem. By contrast, the FAVAR model can extract some basic elements (factors) from a large number of economic indicators to accurately describe related latent macroeconomic variables. Early studies mainly applied the FAVAR method to measure the impact mechanism of monetary policy factors on macroeconomic variables. Bernanke et al. (2005) were the first to use the FAVAR model to extract core macroeconomic variable factors, effectively identifying the effects of US monetary policy. Fernald et al. (2014) also applied this method to analyze the monetary policy of the People's Bank of China. Through the FAVAR method, the authors effectively addressed issues such as data quality and completeness of data sequences, extracted factors such as Chinese economic activity and inflation, and effectively evaluated the effects of different monetary policies. This paper current also attempts to use the FAVAR method to observe changes in a large number of Chinese macroeconomic-related variables in the model.

The final relevant strand of literature is on the global transmission and mutual influence of monetary policies. Numerous studies have investigated the transmission and mutual influence of global monetary policies. Rey (2015), Han and Wei (2018), Kalemli-Özcan (2019), and Gopinath et al. (2020), among others, have examined the transmission of conventional monetary policy. Alpanda and Kabaca (2020) and Kolasa and Wesolowski (2020) have focused on unconventional monetary policy. In contrast to the existing literature, our research explores the transmission of trade risks to macroeconomic variables in the presence of monetary policy.

The subsequent sections of this paper are organized as follows: In Sections 2 and 3, we present detailed explanations of our DHFM and FAVAR models, along with descriptions of the datasets used. Section 4 presents the results of the VAR analysis and provides accompanying insights. Section 5 conducts various robustness checks to validate our main findings. Finally, Section 6 concludes.

2. The DHFM model, data, and trade factors subtraction

2.1. Model

We attempt to structurally decompose different layers of trade factors using a DHFM. We employ the DHFM introduced by Moench et al. (2013), which describes variations within the dynamics of panels and the idiosyncratic noise of specific individuals. We consider the influences of various category factors such as regions and industries; here, we initially aim to investigate the differences resulting from regional factors.

We consider a three-level model here. Let N_r represent the number of countries in region $r = 1,\ldots,R$, let $N = N_1 + \ldots + N_R$ represent the total number of countries, and let the time-series length for each country be T. In this model, the macro variable y_{rnt} depends on several latent factors, including the world factor F_t, regional factors $G_{rt} = \left(G_{r1t}, \ldots, G_{rK_{G_r}t}\right)$, where K_{G_r} is the number of regional factors for region r, and the specific country factor e_{yrnt}:

$$y_{rnt} = \lambda^{n}_{Gr}(L)G_{rt} + e_{yrnt} \tag{1}$$

$$G_{rjt} = \lambda^{j}_{Fr}(L)F_t + e_{Grnt}, \tag{2}$$

where, λ^{n}_{Gr} and λ^{j}_{Fr} are the lag operators for the regional and world factors, respectively, and e_{Grnt} represents regional changes.

Finally, we assume the specific country factor, regional factor, and world factor all follow autoregressive processes with stationary normal distributions of orders q_{yrn}, q_{Gr}, and q_F, respectively.

We extract factors using the Markov Chain Monte Carlo (MCMC) method, and the main steps are as follows:

Table 1
ADF test results for stability of factors.

Factor	h	pValue	stat
World	true	0.001	−22.736
OECD	true	0.001	−23.164
ASEAN	true	0.001	−22.678
Belt & Road	true	0.001	−22.619
Hong Kong & Macau & Taiwan	true	0.001	−21.316
Rest of World	true	0.001	−23.221
Common	true	0.001	−23.846
M&H Tech	true	0.001	−23.564
Low Tech	true	0.001	−22.286
R&E	true	0.001	−23.906
Agriculture	true	0.001	−24.267
Other	true	0.001	−22.853

Notes: This table summarizes the augmented Dickey-Fuller (ADF) test results for various regional and industry factors. "h" indicates whether the null hypothesis of a unit root is rejected ("true" means rejected, confirming the stationarity). "stat" is the ADF test statistic.

1. Data Chunking. Use principal component analysis to obtain the initial values of $\{F_t\}$ and $\{G_t\}$, and from these values, obtain the initial values of $\Lambda = (\Lambda_G, \Lambda_F)$, $\Psi = (\Psi_G, \Psi_F, \Psi_Y)$, and $\Sigma = (\Sigma_G, \Sigma_F, \Sigma_Y)$.
2. Given Λ, Ψ, Σ, and the data of $\{F_t\}$ and y_{rmt}, plot $\{G_t\}$.
3. Given Λ, Ψ, Σ, and $\{G_t\}$, plot $\{F_t\}$.
4. Given $\{F_t\}$ and $\{G_t\}$, plot Λ, Ψ, Σ.
5. Return to step 2.

Further details, including key assumptions and the MCMC method, are provided in Appendix A.

The total unconditional variance for each individual variable can be decomposed according to

$$\mathrm{Var}(y_{rn}) = \gamma'_{Frn}\mathrm{vec}(\mathrm{Var}(F)) + \gamma'_{Grn}\mathrm{vec}(\mathrm{Var}(e_{Gr})) + \mathrm{vec}\left(\mathrm{Var}\left(e_{yrn}\right)\right), \tag{3}$$

where the γ's are functions of loading on factors λ's.The variance share of the world factor is denoted by $Share_{WF}$ and measured as

$$Share_{WF} = \frac{\gamma'_{Frn}\mathrm{vec}(\mathrm{Var}(F))}{\mathrm{Var}(y_{rn})}. \tag{4}$$

A more direct way to decompose the fluctuations of y_{rn} into world, regional, and specific country factors is the method of Del Negro and Otrok (2007):

$$\mathrm{Share}_{\mathrm{WF}} = \frac{\sum_{t=t_0}^{t_1}\left(\lambda^n_{Gr}\lambda^j_{Fr}F_t\right)^2}{\sum_{t=t_0}^{t_1}\left(\lambda^n_{Gr}\lambda^j_{Fr}F_t\right)^2 + \sum_{t=t_0}^{t_1}\left(\lambda^n_{Gr}e_{Grt}\right)^2 + \sum_{t=t_0}^{t_1}\left(e_{yrnt}\right)^2}. \tag{5}$$

This variance-decomposition calculation is applicable to both the full sample and sub-samples for each country.

Factor extraction for the industry group is also operated with the same logic, by replacing the world factor with the common factor, and the five regional factors with 5 Sector Factors.

2.2. Data

For dynamic hierarchical factor subtraction of the region group, we use monthly export data of China to 238 global economies between January 2001 and June 2023 from the CEIC database, with the sample period consistent with the macroeconomic variables. All series are adjusted for the Chinese New Year effect as described by Fernald et al. (2014), and seasonal adjustments are made for data as necessary. For missing values, we use the expectation-maximization (EM) algorithm to handle them.

We divide all economies into five groups: 38 OECD economies, 10 ASEAN economies, 44 Belt & Road countries, 3 economies of rest of Greater China (Hong Kong, Macau, Taiwan), and, finally, 143 economies of the rest of the world. After grouping, we use the DHFM method to extract one world-factor and five regional-factors time-series for the trade data of each economy according to the world-, region-, and country-specific levels.

As depicted in Fig. C.1 both regional and industry factors demonstrate a high degree of stability over time. The plots illustrate the temporal fluctuations of these factors from January 2001 to June 2023. Although each factor exhibits minor fluctuations at certain points, the variations are contained, indicating no significant long-term trends or systematic changes. Subsequently, we conduct a stationary test of these factors using the augmented Dickey-Fuller (ADF) Test, which further substantiates their stability across the observed period. (See Table 1.)

Intuitively, how should we understand the hierarchy of our extracted factors? Taking the three-level factors from the regional

Table 2
Variance Decomposition of Trade Factors - Region.

Group	Name	Percentage		
		World	Region	Country Specific
OECD	United States	27.7 %	27.0 %	45.3 %
	Japan	22.2 %	21.7 %	56.1 %
	Germany	39.1 %	38.2 %	22.7 %
	United Kingdom	38.5 %	37.6 %	23.8 %
	France	36.2 %	35.4 %	28.4 %
ASEAN	Singapore	56.5%	11.1 %	32.4 %
	Vietnam	43.1 %	8.5%	48.4%
	Lao, PDR	14.3 %	2.8%	82.9%
Belt & Road	Russia	42.5%	11.6 %	45.9%
	India	46.2 %	12.6 %	41.2 %
	Saudi Arabia	59.5%	16.2 %	24.3 %
	Iran	28.2 %	7.7 %	64.1 %
	Romania	38.2 %	10.4%	51.4%
	Kazakhstan	29.1 %	7.9%	63.0%
Others	Brazil	42.3 %	15.0%	42.7 %
	Ethiopia	12.0%	4.2 %	83.8%
	Jamaica	21.6 %	7.7 %	70.7 %

Table 3
Variance decomposition of trade factors - industry.

Group	HS 2-digit	Products	Percentage		
			Common	Sector	Industry Specific
M&H-Tech	HS29	Organic chemicals	36.1 %	36.2 %	27.7 %
	HS30	Pharmaceuticals	21.6 %	21.7 %	56.7 %
	HS85	Machinery, electrical equipment, and their parts	31.1 %	31.3 %	37.6 %
	HS87	Vehicles and their parts and accessories	37.5%	37.7 %	24.8%
	HS90	Optical, photographic, cinematographic, measuring, checking, medical or surgical instruments and apparatus	34.4%	34.6 %	31.0%
Low-Tech	HS60	Knitted or crocheted fabrics	84.9%	0.2 %	14.9 %
	HS61	Knitted or crocheted clothing and accessories	69.7 %	0.2 %	30.1 %
	HS64	Footwear, gaiters and the like	66.9%	0.2 %	32.9 %
R&E	HS70	Glass and glassware	75.4%	14.4%	10.2 %
	HS73	Iron and steel products	78.1 %	14.9%	7.0%
Agriculture	HS01	Live animals	12.1 %	7.1 %	80.8%
	HS07	Edible vegetables, roots, and tubers	38.9%	22.9%	38.2 %
	HS10	Cereals	4.4%	2.6 %	93.0%
	HS16	Meat, fish, crustaceans, mollusks, and other aquatic invertebrates, prepared or preserved	54.2 %	31.9%	13.9%

perspective as an example, the world factor can be interpreted analogously to systematic risk in financial markets, reflecting common trends affecting trade across all countries. This interpretation is particularly evident in major global events such as the 2008 financial crisis and the COVID-19 pandemic. Regional factors, meanwhile, capture distinct characteristics of different regions. For instance, OECD and ASEAN countries may experience varying timelines in terms of COVID-19 impact and recovery patterns. ASEAN countries, in particular, might be more susceptible to regional events specific to Southeast Asia, such as local natural disasters.

A similar interpretation applies to the industry perspective. The common factor reflects shocks that universally affect trade across all industries, such as the major disruptions during the COVID-19 pandemic. Meanwhile, sector-specific factors, such as those for medium- and high-tech industries, capture more targeted shocks - for example, the global semiconductor shortage of 2021 that predominantly affected these sectors.

To observe the degree to which different regional economies are influenced by their respective regional factors, we present below the results of the variance decomposition of selected economies to roughly present the contribution of factors at different levels. The first column of the Table 2 indicates the region group to which the economy belongs, the second column shows the name of the economy, and the third column represents the contribution of the world-factor variance, showing significant differences between countries. The fourth column represents the variance contribution of the factors belonging to their respective groups, showing the largest difference contribution in the OECD group. The fifth column represents the contribution of the respective country-specific factors.

For dynamic hierarchical factor subtraction of the industry group, we also use monthly export data from China, from January 2001 to June 2023, from the CEIC database, but select industry data at the HS 2-digit level for 99 categories. The Chinese New Year effect, seasonal adjustments, and handling of missing values are adjusted using methods similar to those used for the region group.

We divide all HS 2-digit-level data into five groups: 21 medium- and high ("M&H")-tech products industries, 31 low-tech products industries, 18 resources and energy ("R&E") industries, 24 agriculture industries, and 4 other industries. After grouping, we use the DHFM method to extract one common-factor and five sector-factors time series for the trade data at the 2-digit HS level according to the three levels of common, sector, and industry-specific.

Similarly, we present below the variance decomposition of selected representative industries in Table 3.

3. The factor-augmented VAR model and data

3.1. Model

We next employ the FAVAR model developed by Bernanke et al. (2005) to examine the impact of trade risks on the macroeconomic landscape. Let X_t ($N \times 1$ vector) denote a plethora of observed macroeconomic time series containing rich economic-condition information. Additionally, we have observed variables T_t ($M \times 1$ vector) representing time series with abundant trade-condition information. Our objective is to investigate the effects of shocks in T_t on X_t. However, employing all sequences from X_t directly in structural VAR analysis is challenging due to the limited observations for each sequence, despite having hundreds of sequences.

Fortunately, numerous studies have affirmed that a few factors can explain the majority of variations in many macroeconomic sequences. Hence, rather than directly employing all macroeconomic sequences, we summarize the information content with a few unobserved factors, denoted by L_t ($K \times 1$ vector). Similarly, because the trade variables T_t encompass numerous sequences, we also extract latent factors denoted by Y_t. Additionally, we include two control variables—monetary policy rates for China and the US, represented by Z_t ($J \times 1$ vector) in the VAR system to control for factors at the policy level. We assume the dynamics of Z_t, L_t, and Y_t follow this transition equation:

$$\begin{pmatrix} Z_t \\ L_t \\ Y_t \end{pmatrix} = \Phi(L) \begin{pmatrix} Z_{t-1} \\ L_{t-1} \\ Y_{t-1} \end{pmatrix} + \varepsilon_t. \tag{6}$$

$\Phi(L)$ is a polynomial of lag operators, and ε_t is the error term with a mean of zero and covariance matrix Σ. We assume the error term can be represented as a linear combination of structural shocks: $\varepsilon_t = P \cdot U_t$. The matrix P is the Cholesky decomposition of the variance-covariance matrix. The structural shocks U_t represent shocks related to trade risks.

However, Eq. (6) cannot be estimated directly because the factor L_t is unobservable. We further assume a relationship exists between our macroeconomic sequences X_t and the latent factor L_t, as well as the observed trade-risk indicators Y_t, represented by the observation equation:

$$X_t = \Lambda^L L_t + \Lambda^Y Y_t + e_t. \tag{7}$$

Because the factor L_t is unobservable, it is replaced by $\widehat{L}_t$, estimated from over 131 Chinese macroeconomic variable sequences. The estimation is divided into two steps. First, we extract principal components $\widehat{C}_t$ from X_t. All principal components are normalized to have unit variances. Second, to ensure identification of the VAR system used later, we remove direct dependencies of the factor $\widehat{C}_t$ on Y_t and recursively identify trade shocks. To do so, we categorize all macro variables into two types: fast-moving variables and slow-moving variables. Variables that are predominantly predetermined at the current period, such as industrial production, unemployment and so on, are categorized as slow-moving. Variables that are highly sensitive to current economic news or shocks, such as asset prices, are categorized as fast moving. The slow-moving factor $\widehat{L}_t^s$ is estimated as the principal component of all slow-moving variables and assumed to be unaffected by contemporaneous shocks related to trade risks. Then, as shown in regression Eq. (8), we regress the common principal components of all macro sequences on trade risks and the slow-moving component to obtain estimates of the coefficients b_{F^s} and b_Y:

$$\widehat{C}_t = b_{F^s} \widehat{L}_t^s + b_Y Y_t + e_t. \tag{8}$$

The lagged terms of $\widehat{L}_t$ required for the subsequent VAR analysis are constructed from $\widehat{C}_t - \widehat{b}_Y Y_t$.

This model setup allows us to capture three key economic mechanisms: (1) the direct transmission of trade shocks through observable channels (Y_t), (2) the broader macroeconomic spillovers through latent factors (L_t), and (3) the policy responses through monetary channels (Z_t). This structure is particularly suitable for analyzing China's economy, where trade shocks can affect the economy through both direct trade linkages and indirect channels such as business confidence and investment decisions.

3.2. VAR specification and shock identification

Our VAR system consists of 10 variables: six trade factors (extracted using the aforementioned DHFM method as region and industry groups separately), two latent factors representing Chinese macroeconomic indicators (extracted from over 130 macroeconomic variables), the US monetary policy rate, and the Chinese monetary policy rate. The FAVAR method is suitable for us because we want to understand how the trade factor affects the Chinese economy at a macro level and observe the role of US-China monetary policies in this transmission mechanism. Because all sequences contain information related to the Chinese macroeconomy, we prefer to use all sequences rather than selecting only those variables we consider important.

The monetary policy variables in our FAVAR framework serves both as control variables and as important channels through which trade shocks are transmitted. This approach allows us to disentangle the direct effects of trade shocks from their indirect effects working through monetary policy responses, providing a more complete picture of the transmission mechanisms.

We use monthly data from January 2001 to June 2023. Based on various criteria such as the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn (HQ) statistics, we decide to use a VAR system with one lag.

As previously mentioned, we order the variables in the VAR system from exogenous to endogenous. The ordering of variables from exogenous to endogenous reflects the economic structure where trade factors ($Tf1$ to $Tf6$) are considered more exogenous due to China's role as a price taker in many international markets. The domestic factors ($CNf1$, $CNf2$) are ordered after trade factors because they respond to external shocks within the same period. Monetary policy rates are ordered last, consistent with the assumption that policymakers observe and respond to both external and domestic conditions.

Additionally, we identify the shock that we are most interested in, namely, the shock in the trade factor, and we assume other factors do not have a contemporaneous response to the trade factor. We achieve the identification of structural shocks by imposing short-term constraints on the responses of variables.

$$\varepsilon_t = P \times U_t = \begin{bmatrix} \times & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \times & \times & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \times & \times & \times & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \times & \times & \times & \times & 0 & 0 & 0 & 0 & 0 & 0 \\ \times & \times & \times & \times & \times & 0 & 0 & 0 & 0 & 0 \\ \times & \times & \times & \times & \times & \times & 0 & 0 & 0 & 0 \\ \times & \times & \times & \times & \times & \times & \times & 0 & 0 & 0 \\ \times & \times & \times & \times & \times & \times & \times & \times & 0 & 0 \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & 0 \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \end{bmatrix} \times \begin{bmatrix} u_t^{Tf1} \\ u_t^{Tf2} \\ u_t^{Tf3} \\ u_t^{Tf4} \\ u_t^{Tf5} \\ u_t^{Tf6} \\ u_t^{CNf1} \\ u_t^{CNf2} \\ u_t^{USmp} \\ u_t^{CNmp} \end{bmatrix} \tag{9}$$

The VAR system will be estimated through ordinary least squares (OLS) regression, from which we can obtain coefficients for the impulse responses of all variables in the VAR system to trade-risk shocks. By utilizing these coefficients and Eq. (6), we can infer the impulse responses of all macroeconomic variables in X_t to trade-risk shocks.

3.3. Data and estimation

Regarding macro variables, we use 131 monthly Chinese macroeconomic series listed in the Appendix. All series are taken from CEIC China Premium Database and are at the monthly frequency. Our sample period spans from January 2001 to June 2023, balancing data availability, external validity, and keeping the analysis up to date. Consistent with the trade variables mentioned earlier, Chinese New Year effects are all handled. Seasonality adjustment is performed using the US Census Bureau's X-13 program: SA = seasonally adjusted, NS = no seasonal adjustment. The transformations are Δ-first difference, ln-logarithm, Δln-first difference of logarithm, and none-no transformation. All variables are also labeled as fast or slow according to their rate of change. The classification of variables into fast-moving and slow-moving categories reflects their different adjustment speeds to economic shocks. Slow-moving variables (e.g., industrial production and employment) typically face various frictions and adjustment costs, whereas fast-moving variables (e.g., financial market indicators) can respond immediately to new information. To address numerous missing values, we employed the EM algorithm. Each variable is assumed to be either fast moving or slow moving for the purpose of FAVAR estimation.

Regarding monetary policy, for China's monetary policy, we employed the most active money market rate, R007, which effectively reflects the central bank's targeted interest rate. For US monetary policy, we used the effective federal funds rate. Additionally, to incorporate unconventional monetary policy during the zero-lower-bound period, we replaced relevant rates with the shadow rate proposed by Wu and Xia (2016).

4. Results

Based on the DFM, we try two different extraction methods; that is, we use variables from the region group and the industry group, respectively, as trade variables in the FAVAR model, conducting FAVAR analyses for both groups. Each group consists of six variables, two macro variables, and two monetary policy variables included in the FAVAR.

4.1. Impulse responses to trade variables: Roles of region and industry

We started with the region group, where we first arrange the variables in the overall variable ranking according to the order from most exogenous to most endogenous, as mentioned earlier, that is, trade variables, latent macro variables, US monetary policy, and

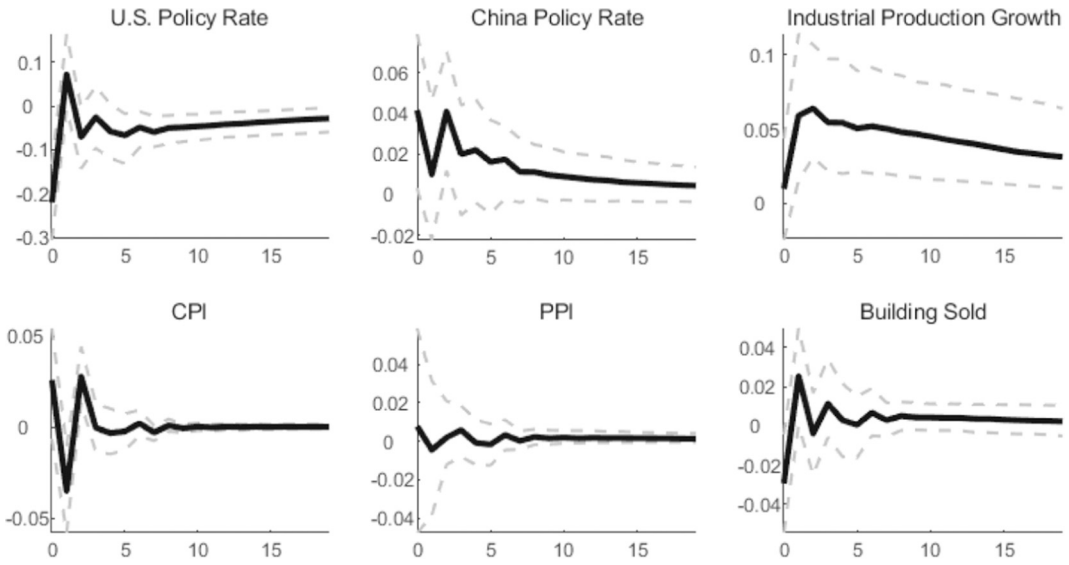


Fig. 1. Impulse responses to the world factor (I).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

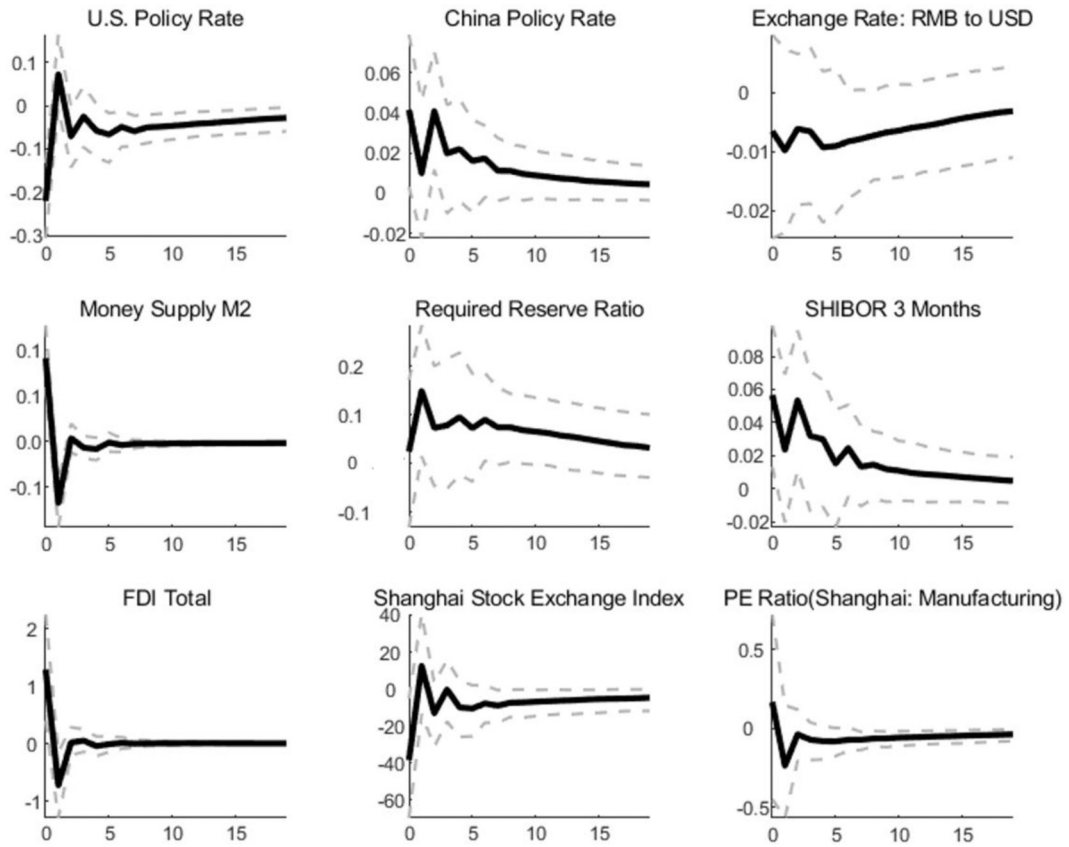


Fig. 2. Impulse responses to the world factor (II).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

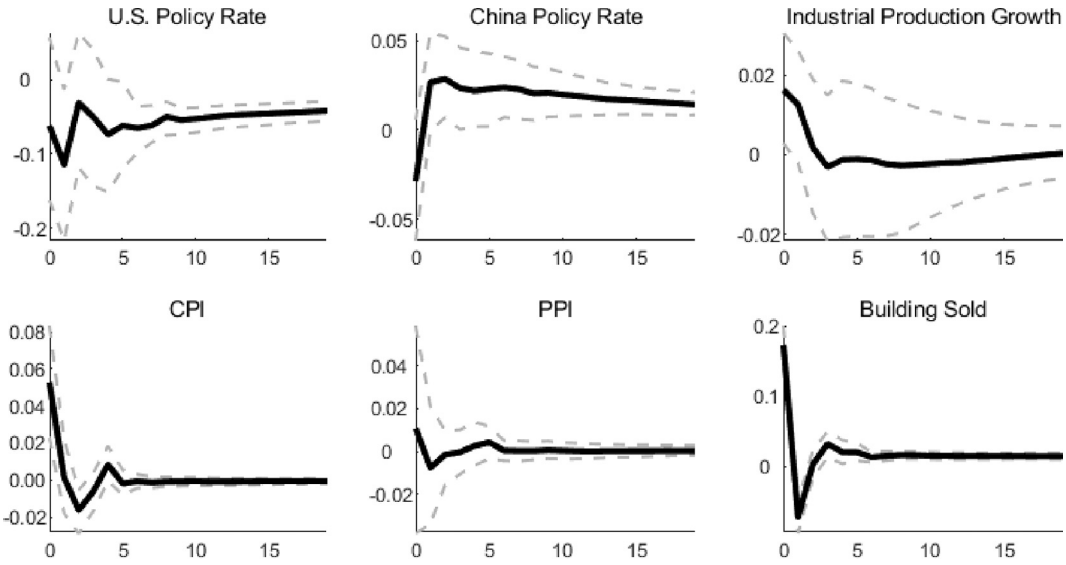


Fig. 3. Impulse responses to an industrial common shock (I).
Notes: Impulse responses to an industrial common shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

Chinese monetary policy. We sort the trade variables according to the following economies: world, OECD, ASEAN, Belt & Road, rest of the world, and rest of Greater China. This distinction is based on the size of trade between different economic groups and China. For example, in 2022, China's exports to OECD countries, ASEAN countries, and the remaining Belt & Road countries accounted for approximately 51.9%, 15.8%, and 13.4% of the total exports, respectively, highlighting their importance. Therefore, in the VAR results, we also separately examined the impulse responses to shocks of the world, OECD, and ASEAN factors on other variables. The specific results regarding the world factor are shown in Figs. 1 and 2.

The impact of a positive world-factor shock reveals interesting policy divergence and economic transmission mechanisms. The shock triggers different monetary policy responses between China and the US, with US policy rates initially decreasing while China's policy rates rise. This asymmetric policy response reflects the different positions of these economies in global trade and their distinct policy objectives. For China, the policy-rate increase likely represents a preemptive move to maintain financial stability amid increased capital flows. The shock generates sustained positive effects on China's industrial production, suggesting enhanced external demand benefits the real economy. Meanwhile, the RMB appreciation and increased M2 supply, coupled with rising required reserve ratios and Shibor rates, indicate active liquidity management by Chinese authorities. The increase in foreign direct investment (FDI) inflows further supports the positive trade environment, although a stock market decline might reflect a portfolio reallocation effect. Notably, the limited response of price indicators (CPI and PPI) and buildings sold suggests the transmission of global trade shocks might be partially buffered by China's policy framework.

The OECD-factor shock triggers notably different economic dynamics than the world factor, as shown in Figs. C.2 and C.3. Both China and the US respond with monetary tightening, reflecting the shock's inflationary nature as evidenced by the initial positive responses in both CPI and PPI in China. The contractionary monetary stance, manifested in rising policy rates and Shibor, along with decreasing M2, appears to be a response to these inflationary pressures. The RMB depreciation, coupled with a slight increase in FDI, indicates complex capital flow dynamics. The significant stock market appreciation, despite tighter monetary conditions, might reflect investors' positive sentiment about China's economic resilience or potential benefits from OECD economic activities. The temporary positive response in buildings sold suggests some spillover to domestic demand, though this effect appears to be short lived.

The ASEAN-factor shock demonstrates distinct transmission patterns, as illustrated in Figs. C.4 and C.5, particularly in terms of monetary policy divergence between China and the US. While the US tightens monetary policy, China opts for monetary easing, suggesting different risk-return trade-offs in managing regional economic linkages. This policy divergence reflects China's strategic response to ASEAN-related shocks, possibly aimed at supporting trade relationships with this crucial regional partner. The economic effects are mixed: industrial production shows initial improvement before turning negative, whereas both CPI and PPI experience mild upward pressure initially. The increase in buildings sold suggests positive spillovers to domestic demand. On the financial front, despite a brief RMB depreciation, both FDI inflows and stock market performance improve, indicating positive investor sentiment towards China-ASEAN economic integration. These dynamics align with ASEAN's growing importance as China's largest trading partner since 2020, characterized by both agricultural and energy imports and expanding export opportunities. The relationship's significance is underscored by historical data from the National Bureau of Statistics, showing China-ASEAN trade growth averaging 8.8% annually since 2013, exceeding China's overall growth rate by 3.8 percentage points during the same period. These empirical findings support the strategic value of deepening economic ties with ASEAN economies.

Next, we check the response of the industry group. Similar to the region group, we choose to order the variables as common,

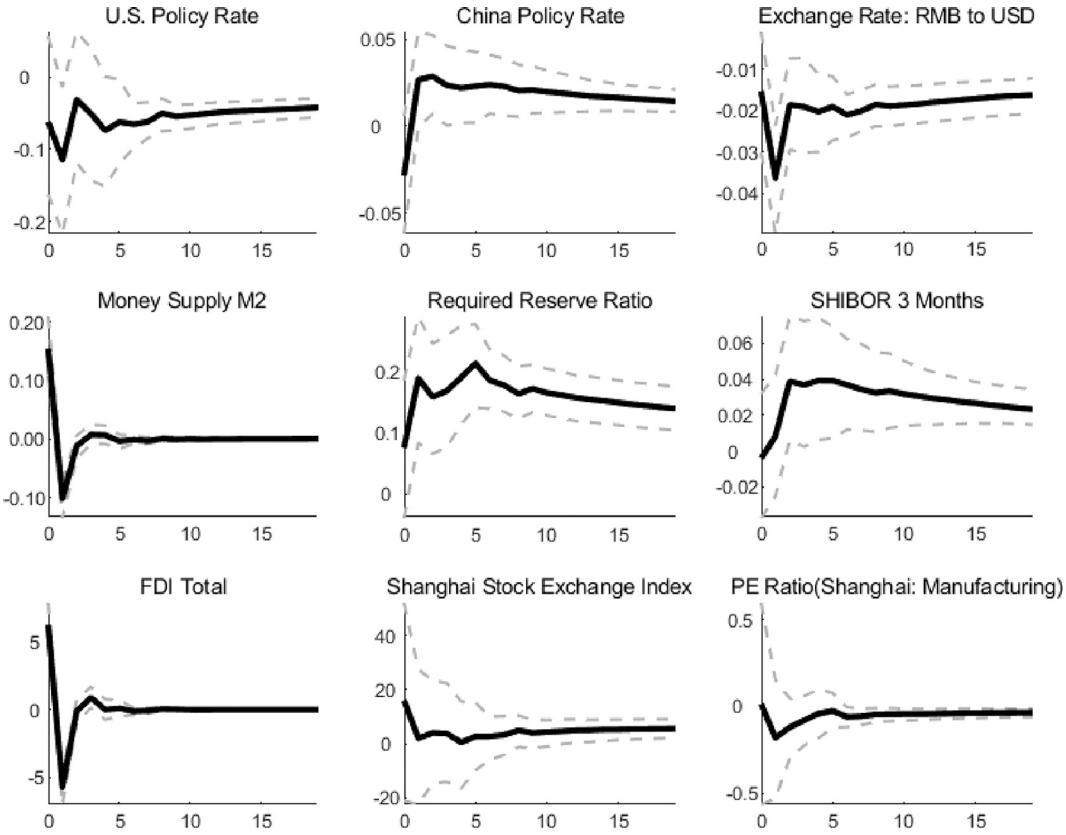


Fig. 4. Impulse responses to an industrial common shock (II).
Notes: Impulse responses to an industrial common shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

"M&H"-tech products, low-tech products, mining and energy, agriculture, and others. This order also reflects the importance of different categories of exports. In 2022, the export proportions of these five categories of goods from China were 61.39%, 20.55%, 13.19%, 2.70%, and 2.18%, respectively. For the impulse response, we examine the effects of the common, M&H-tech, and low-tech-factors, as shown in Figs. 3, 4, and C.6-C.9.

The impulse-response analysis reveals the common factor from industrial decomposition exhibits remarkably similar patterns to the world factor identified in the region group. Following a positive shock, both factors trigger expansionary effects: industrial production increases, inflation pressures emerge with rising CPI, and real estate activities strengthen as reflected in building sales. In the financial markets, we observe RMB appreciation, M2 expansion, and moderate gains in the stock market. The policy responses also show consistent patterns, with the US Federal Reserve implementing accommodative monetary policy while China maintains a prudent stance through slight interest rate adjustments and reserve requirement ratio management.

Note the world trade factor extracted from the regional dimension and the common factor extracted from the industrial dimension show certain similarities in their impacts. This similarity is reasonable because both factors capture the highest level of common shocks affecting China's exports, albeit through different transmission channels. Specifically, the world trade factor derived from regional decomposition primarily captures demand-side shocks transmitted through market access (Caliendo et al., 2018), whereas the common factor from industrial decomposition reflects more of the supply-side shocks transmitted through industrial chain linkages (Foerster et al., 2011). This dual-perspective approach enables us to better understand how international trade shocks affect the Chinese economy through different channels.

Regarding the impact of the M&H-tech factor, as shown in Figs. C.6 and C.7, the results reveal distinctive patterns. Whereas price levels remain stable with slight PPI increases, industrial production shows sustained growth, particularly in the medium to long term. In the financial markets, despite accommodative monetary policies in both China and the US, increasing FDI inflows and RMB appreciation, the stock market shows unexpected weakness. This finding might reflect market concerns about capital intensity in high-tech industries, even as fundamental growth remains positive.

These findings suggest M&H-tech industries are crucial for sustainable economic growth, aligning with the concept of "new quality productive forces (NQPF)." Although supporting these industries may involve market uncertainties (as reflected in stock performance), the sustained industrial growth and positive FDI trends validate this strategy. The establishment of the ChiNext and STAR Boards, with their accommodative listing requirements for technology companies, represents an appropriate policy response that maintains its

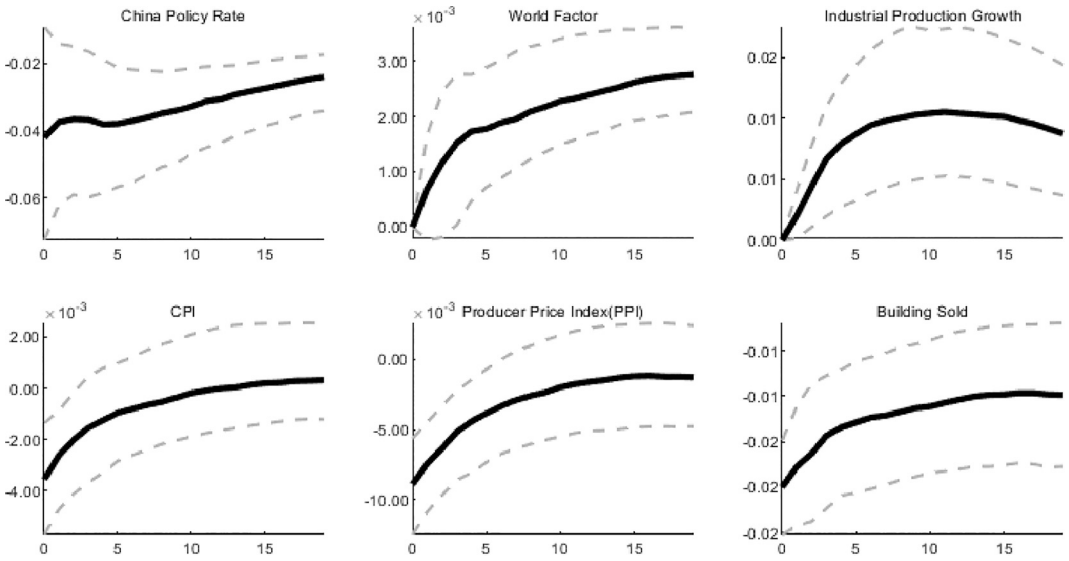


Fig. 5. Impulse responses to a US monetary policy shock (I).
Notes: Impulse responses to a trade shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

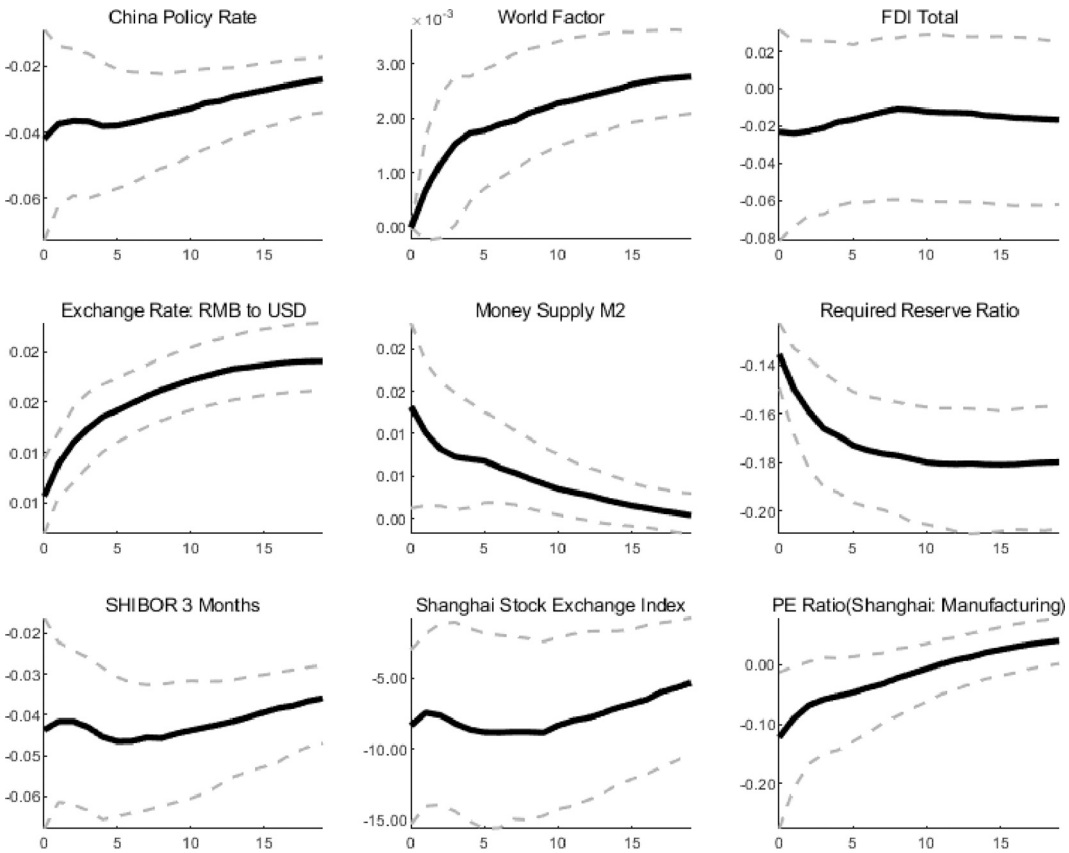


Fig. 6. Impulse responses to a US monetary policy shock (II).
Notes: Impulse responses to a trade shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

strategic significance for China's economic transformation.

As for the low-tech factor, Figs. C.8 and C.9 reveal several important findings. The results indicate a modest increase in industrial production alongside deflationary pressure in producer prices. Both China and the US respond with monetary tightening. The factor triggers negative responses in multiple areas: declining real estate sales, RMB depreciation, and reduced FDI inflows, though interestingly, the stock market shows resilience with positive performance. However, considering the variance decomposition discussed earlier, the low-tech factor explains only a small portion of overall variance, with these industries being more strongly coupled with the common factor. Therefore, although the sector-specific effects are notable, their economic impact remains limited in the broader context.

Overall, the impulse responses to the region group variables reveal distinct patterns. The OECD factor shows notable differences from the world factor, characterized by monetary tightening in both China and the US, inflationary pressures, and positive stock market performance despite tighter monetary conditions. The ASEAN factor demonstrates unique transmission patterns, particularly in terms of monetary policy divergence, reflecting China's strategic response to regional economic linkages. The industry group results reveal that although China's support for the M&H-tech sector may face short-term challenges, including market uncertainties and temporary negative impacts on some indicators (particularly in stock market performance), the sector shows sustained industrial growth and maintains strong development potential through positive FDI trends. On the other hand, the growth of the low-tech sector, while showing some positive signals in stock market performance, does not demonstrate strong positive implications for China's current economy when considering its limited contribution to overall variance.

4.2. Impulse reponses to key control variables: US and China monetary policy

For control variables, we also examine the impact of US and Chinese monetary policy shocks as impulse senders. To avoid over-identification issues, we only incorporate the world factor for the region group and the common factor for the industry group into the VAR model.

The inclusion of monetary policy shocks in our analysis is theoretically motivated and empirically relevant for several reasons. First, monetary policy plays a crucial role in the transmission of trade shocks through exchange-rate channels and financial conditions. Second, as China becomes more integrated into global markets, the interplay between trade shocks and monetary policy responses becomes increasingly important for understanding economic adjustments. Third, the inclusion of both US and Chinese monetary policies helps us better understand how trade shocks interact with different policy regimes, given China's significant role in global trade and the US dollar's dominance in international trade settlement.

Regarding the impact of US monetary policy shocks, we present the scenarios when the world factor is included in the model in Figs. 5 and 6 below. And the impulse responses to the US monetary policy shock with the industrial common factor are shown in Figs. C.10 and C.11, where we see contractionary US monetary policy generates similar effects in both models. Whereas China responds with monetary easing, the world factor and industrial production initially decline before showing signs of recovery. The shock leads to broad-based negative impacts on China's economy, suppressing inflation indicators (both CPI and PPI), real estate transactions (buildings sold), FDI inflows, and the RMB exchange rate. The stock market also experiences downward pressure, indicating the negative spillover effects from US monetary tightening outweigh any potential benefits from China's accommodative monetary stance.

Regarding the impact of Chinese monetary policy shocks, we present the scenarios when the world factor and common factor are included in the model in Figs. C.12 - C.15. The effects of China's contractionary monetary policy are similar in both models. The shock coincides with US monetary tightening. Though the trade factors show limited response, the shock generally leads to subdued performance across most economic indicators. However, somewhat counterintuitively, the stock market demonstrates positive performance, possibly reflecting the preventive nature of China's monetary tightening aimed at maintaining economic stability.

Overall, our analysis reveals significant asymmetries in the transmission and effectiveness of monetary policies between the US and China. US monetary policy demonstrates substantial influence over China's economic dynamics, with its effects propagating through multiple channels including trade, financial markets, and domestic economic indicators. The transmission of US monetary policy shocks shows consistent patterns across different model specifications, highlighting the robustness of these relationships.

By contrast, Chinese monetary policy exhibits more nuanced effects, primarily functioning as a stabilizing force. The policy responses are characterized by their preventive nature rather than aggressive intervention, aligning with China's official stance of maintaining a "prudent" monetary policy framework. This approach helps buffer against external shocks and maintains economic stability, while also revealing certain constraints in policy effectiveness, particularly in addressing trade-related challenges.

The analysis of monetary policy shocks enriches our understanding of trade-shock transmission through several important dimensions. First, it illuminates the complex interplay between external shocks and domestic policy responses, particularly relevant given China's deep integration into global markets. Second, the asymmetric effects of US and Chinese monetary policies underscore the importance of considering global financial conditions in domestic policy formulation. Third, the interaction between trade factors and monetary policies reveals the delicate balance required in maintaining external stability while pursuing domestic economic objectives. These findings suggest that while China has developed sophisticated policy tools to manage external shocks, the effectiveness of these tools varies significantly depending on the nature and source of the shocks.

5. Robustness

We conduct two main robustness checks. First, we examine whether our findings remain consistent in the pre-US-China trade-war period, because the trade conflict might have fundamentally altered the relationships we identified. Second, we test the sensitivity of

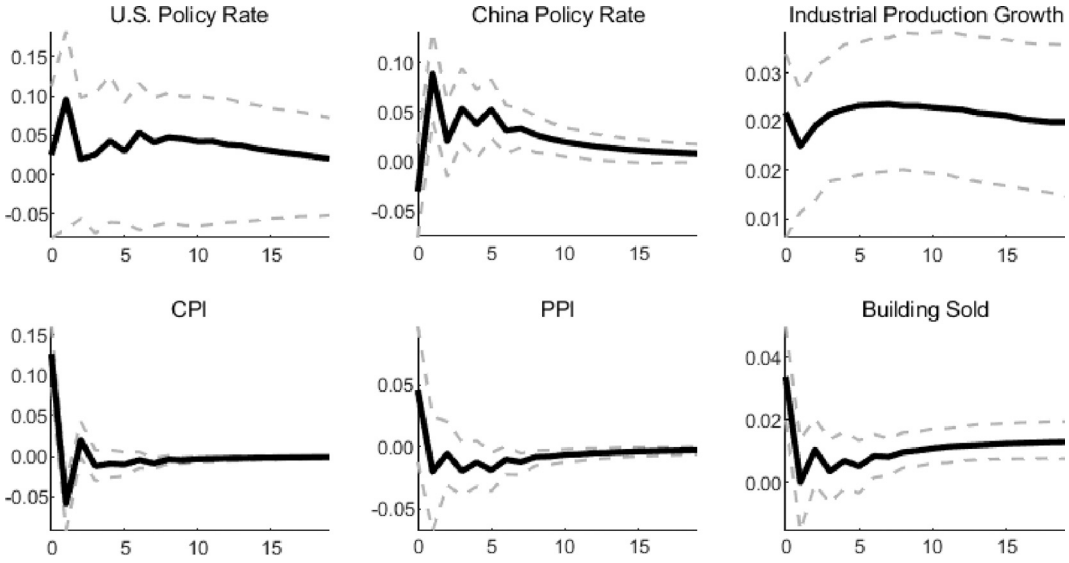


Fig. 7. Impulse responses to the world factor (before the US-China trade war) (I).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

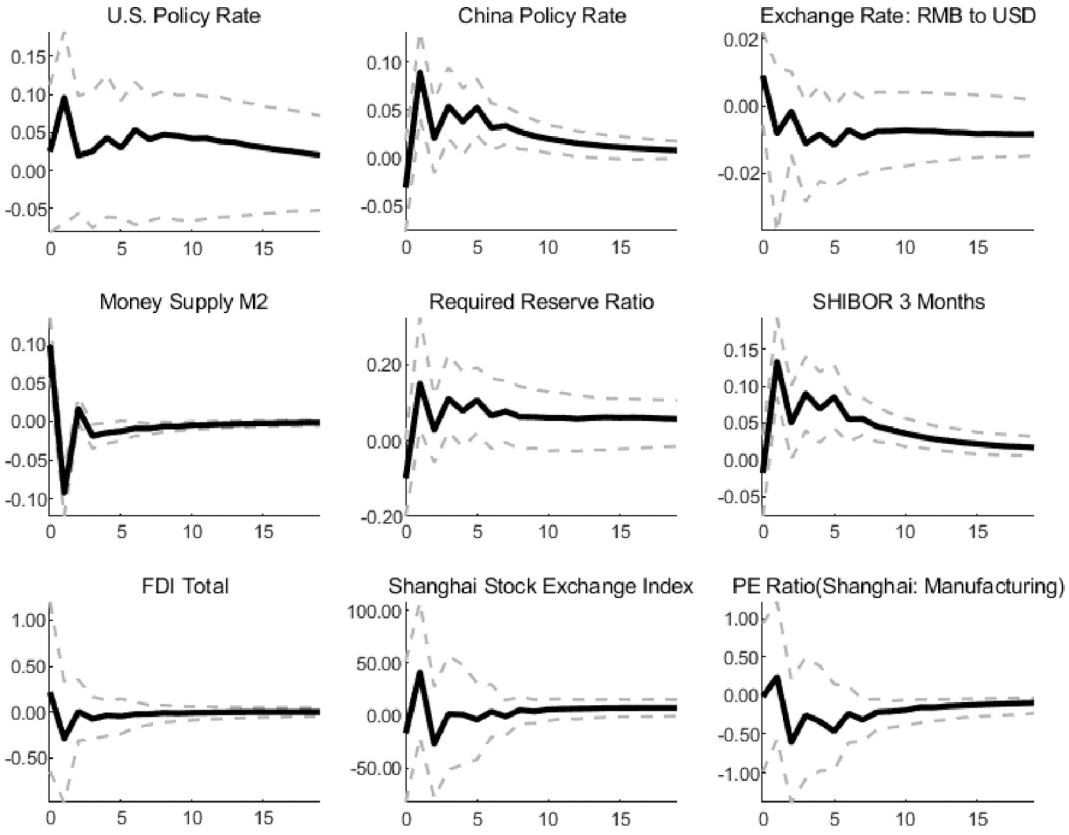


Fig. 8. Impulse responses to the world factor (before the US-China trade war) (II).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

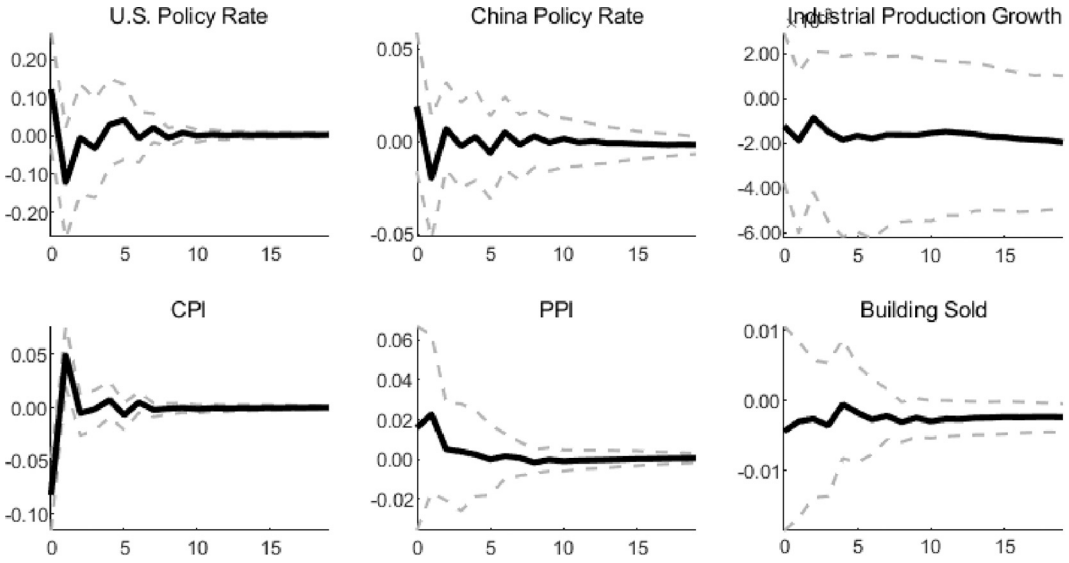


Fig. 9. Impulse responses to an industrial common shock (before the US-China trade war) (I).
Notes: Impulse responses to an industrial common shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

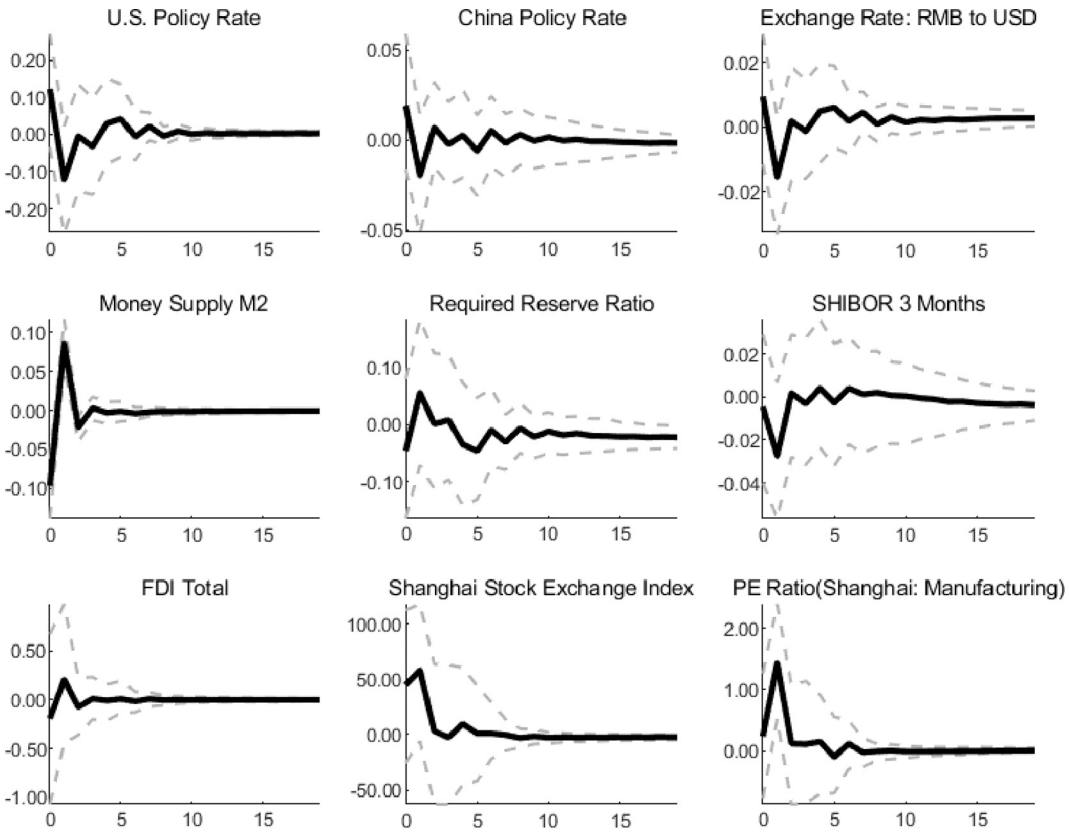


Fig. 10. Impulse responses to an industrial common shock (before the US-China trade war) (II).
Notes: Impulse responses to an industrial common shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

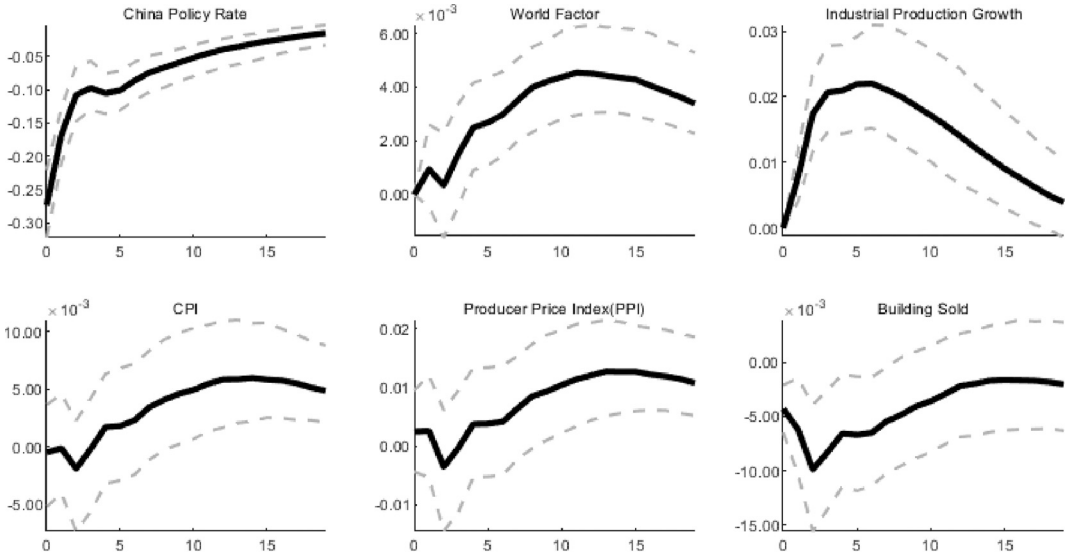


Fig. 11. Impulse responses to a US monetary policy shock (before the US-China trade war) (I).
Notes: Impulse responses to a trade shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

our results to alternative variable orderings in the FA-VAR model.

5.1. *The subsample since the beginning of the US-China trade conflict*

To examine the robustness of our findings, we re-estimate the model using a subsample that begins before the onset of the US-China trade conflict. This period may cause heightened trade tensions and significant policy shifts, which may have affected the macroeconomic dynamics captured in our model.

We define the beginning of the US-China trade conflict as the date when the major tariff impositions were announced, which occurred in the March of 2018, so we divide the full data into two parts: data before the trade war and data after the trade war. By focusing on this subsample before the trade war, we aim to capture the potential structural changes and their impacts on the macroeconomic variables. Here, we have some results of the impulse responses of the impact regionally and industrially shown in Figs. 7–10. The results of the impacts of the OECD factor and the ASEAN factor are shown in Figs. C.16-C.19. And the results of the impacts of the M&H-tech and low-tech factors are shown in Figs. C.20-C.23.

Our subsample analysis reveals patterns largely consistent with the full-sample results. The impulse responses maintain similar shapes and magnitudes, suggesting our findings are not driven by the structural changes brought about by the trade conflict. This consistency across different sample periods strengthens the validity of our main conclusions.

Then, we also test the robustness of the impact of US and Chinese monetary policy shocks as impulse senders. We show some results shown in Figs. 11 and 12. If we consider the monetary policy shock with the industrial common factor and China's monetary policy shock, the results are shown in Figs. C.24-C.29.

5.2. *Alternative ordering in FAVAR model*

The identification of structural shocks in our FAVAR model relies on the Cholesky decomposition, which assumes a specific ordering of variables from most exogenous to most endogenous. To verify that our results are not sensitive to this assumption, we experiment with alternative orderings, particularly focusing on the relative positioning of trade factors and macroeconomic variables.

In our baseline model, we assume a specific ordering of the observed macroeconomic variables and the latent factors from exogenous to endogenous. To test the robustness of our results, we experiment with different orderings, such as changing the order of trade factors and macroeconomic factors, ensuring the core conclusions are not sensitive to these assumptions. Here, we provide results of the impulse responses of the impact regionally and industrially shown in Figs. 13–16. The results of the impacts of the OECD factor and the ASEAN factor are shown in Figs. C.30-C.33. And the results of the impacts of the M&H-tech and low-tech factors are shown in Figs. C.34-C.37.

By re-estimating the FAVAR model with alternative orderings, we find the primary conclusions regarding the effects of trade risks on macroeconomic variables remain robust. Although some variations exist in the subsequent dynamic patterns, the initial shapes of impulse responses are largely consistent with our baseline model. Specifically, the immediate responses and directional patterns of key economic indicators to trade shocks maintain similar characteristics across different orderings, lending credibility to our main empirical findings.

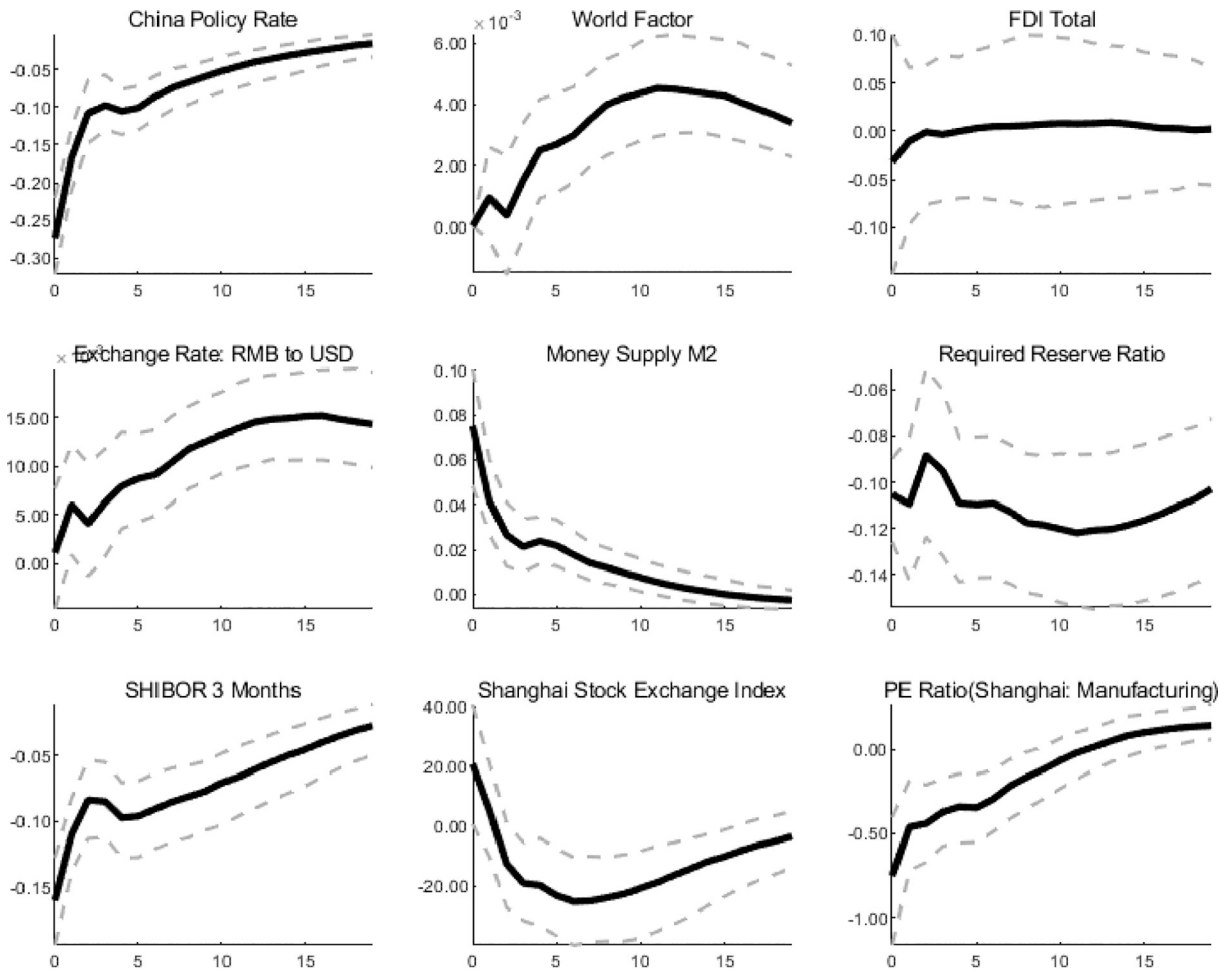


Fig. 12. Impulse responses to a US monetary policy shock (before the US-China trade war) (II).
Notes: Impulse responses to a trade shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

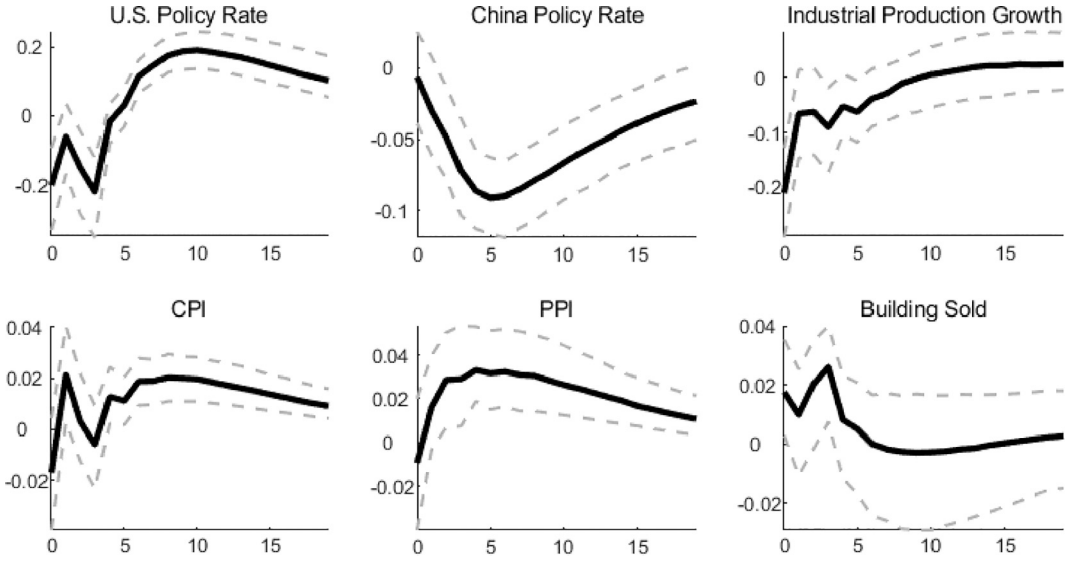


Fig. 13. Impulse responses to the world factor (alternative order) (I).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

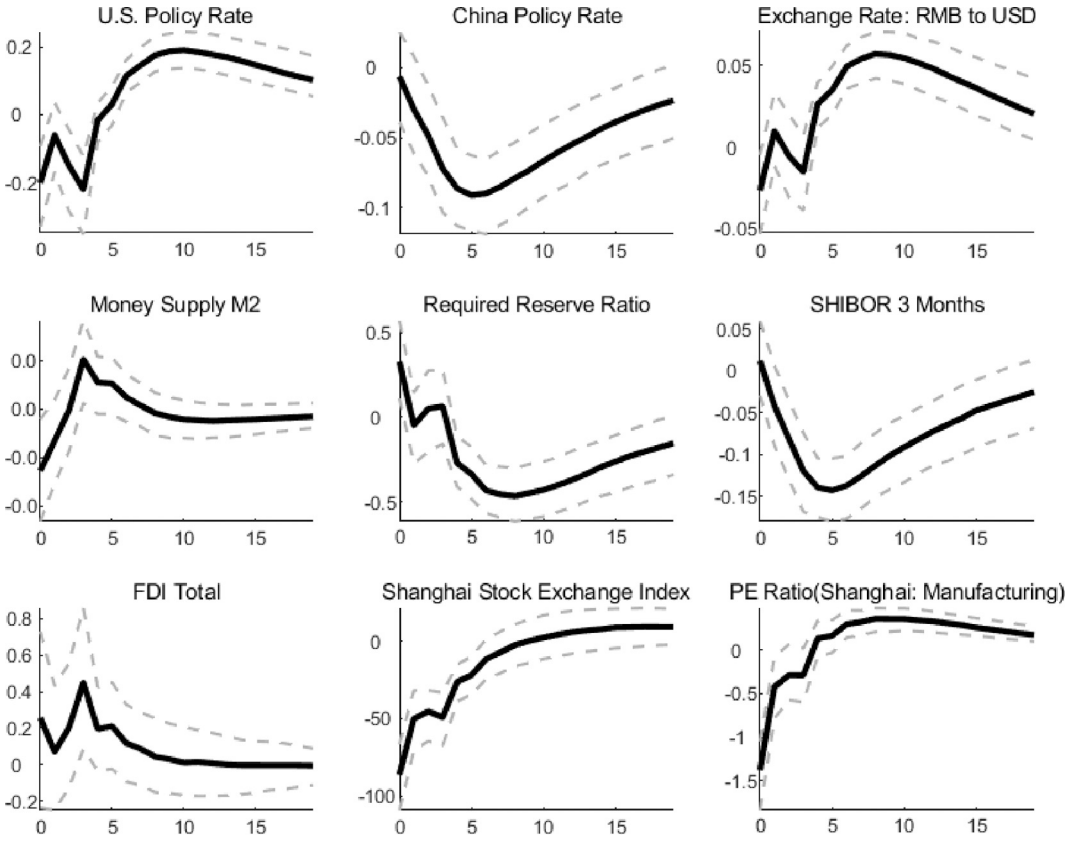


Fig. 14. Impulse responses to the world factor (alternative order) (II).
Notes: Impulse responses to the world factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

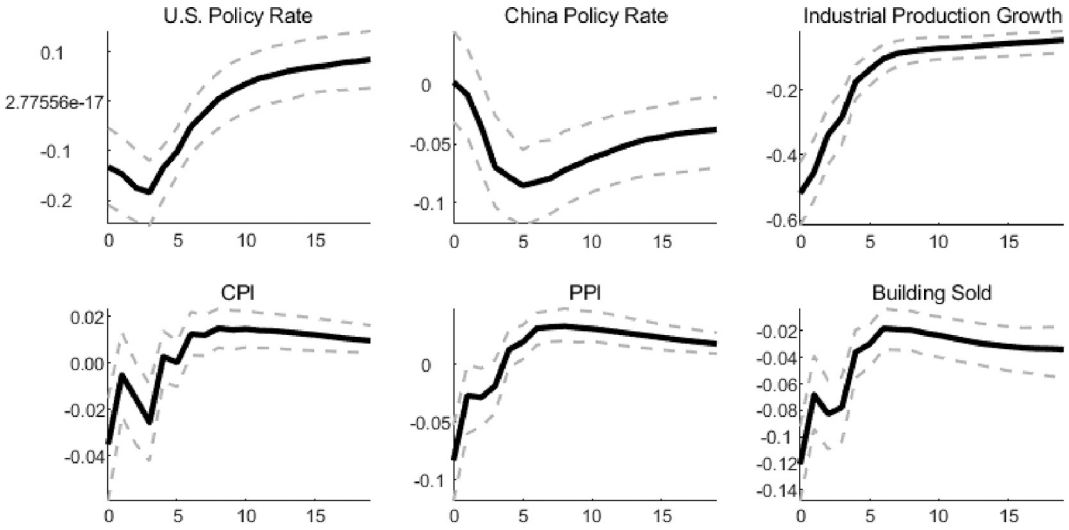


Fig. 15. Impulse responses to an industrial common shock (alternative order) (I).
Notes: Impulse responses to an industrial common shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

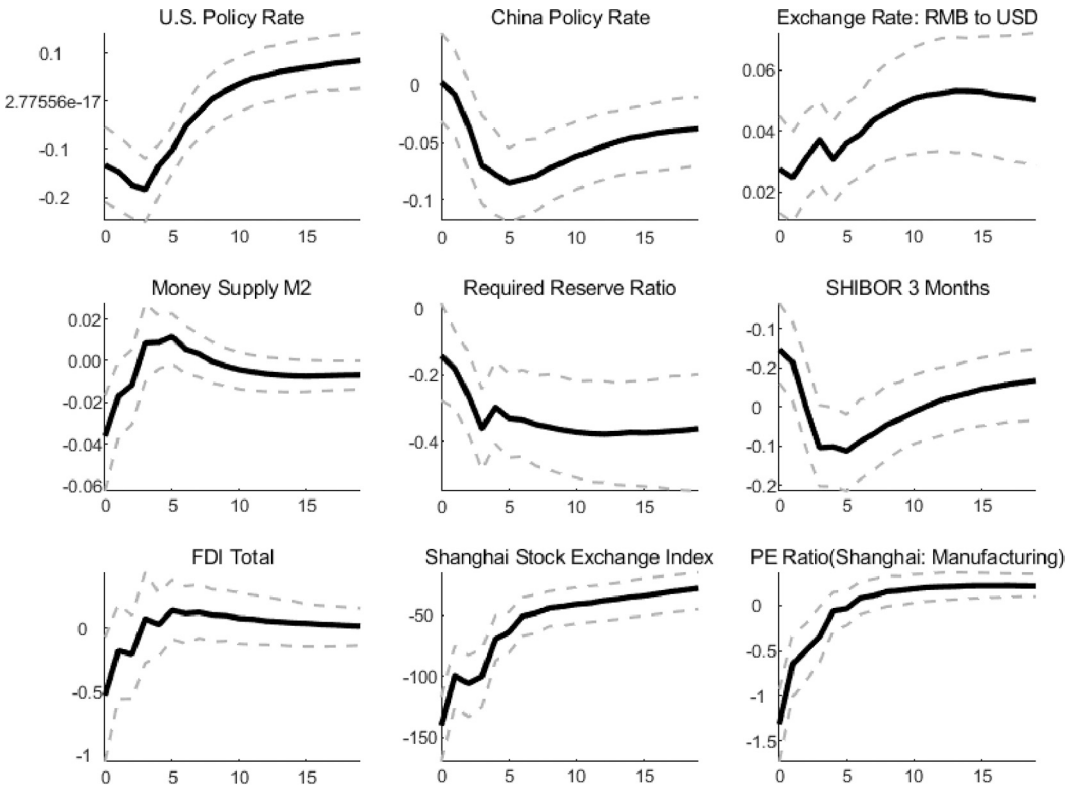


Fig. 16. Impulse responses to an industrial common shock (alternative order)(II).
Notes: Impulse responses to an industrial common shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

These results confirm the stability and reliability of our model. The subsample analysis and alternative ordering in the FAVAR model both support our initial conclusions, reinforcing the link between trade risks and macroeconomic dynamics.

6. Conclusion

The study employs the DHFM method to extract factors from trade data based on the perspectives of region and industry. Subsequently, we use the FAVAR method to incorporate these trade factors into a FAVAR model, along with macroeconomic variables and monetary policy variables, to examine the impulse-response dynamics. The key findings of this study are summarized as follows:

First, regarding overall trade dynamics, variables such as the world factor and the common factor demonstrate positive and significant impacts on China's macroeconomy. This finding underscores the crucial role of maintaining open trade policies and actively promoting foreign trade engagement for China's economic development.

Second, in terms of regional trade patterns, our analysis reveals heterogeneous effects across different trading partners including OECD, ASEAN, and Belt & Road countries, though the aggregate impact remains positive. The findings suggest that while facing increasing trade protectionism from some developed economies, diversifying trade relationships beyond traditional developed markets can foster mutual economic growth among developing economies and benefit China's economic development.

Third, from an industrial perspective, medium-high-technology industries demonstrate robust positive effects on economic variables, particularly showing stronger and more persistent impacts than other sectors. The analysis suggests strengthening the development of medium-high-technology industries could enhance both trade competitiveness and economic resilience.

Fourth, regarding monetary policy transmission, US monetary policy continues to be a significant driver of China's economic cycles, whereas China's monetary policy exhibits a more measured approach, primarily oriented towards countercyclical adjustments and stability maintenance.

Finally, our robustness checks further validate these findings through two approaches. The subsample analysis covering the period before the US-China trade war demonstrates our key results are not driven by recent trade tensions, because the fundamental relationships between trade factors and macroeconomic variables remain stable. Additionally, tests using alternative variable orderings in the FAVAR model confirm our conclusions are not sensitive to identification assumptions, particularly regarding the immediate responses and directional patterns of key economic indicators to trade shocks.

Overall, our findings underscore that trade expansion continues to be a significant positive driver for China's macroeconomic development, even in the face of current global challenges. The results suggest two key strategic implications: first, the importance of diversifying trade relationships across different regions and markets; second, the potential benefits of prioritizing medium-high-technology industrial development. Although China's monetary policy has traditionally focused on stability, our analysis indicates maintaining policy flexibility could be beneficial in responding to evolving trade dynamics and external challenges.

Appendix A. Details on dynamic hierarchical factor model (DHFM)

In this section, we show the detailed derivation for the model in Section 2.

A.1. Identification assumptions

To ensure the proper identification of factors in the Dynamic Hierarchical Factor Model (DHFM), we make the following assumptions:

- **Orthogonality Assumption**: The world factor F_t, regional factors G_{rt}, and country-specific factors e_{yrnt} are assumed to be orthogonal. Thus, the covariances between these factors are zero, ensuring they capture independent sources of variation in the data.
- **Factor-Loading Constraints**: The factor-loading matrices λ_{Gr}^{n} and λ_{Fr}^{j} are subject to constraints to prevent indeterminacy in the model. Specifically, certain elements of these matrices are fixed to zero, which helps in uniquely decomposing the observable variables into underlying factors. This practice is common in factor models to ensure the factors are identifiable and not arbitrarily rotated.
- **Stationarity and Normality Assumptions**: We assume all factors, including the world factor F_t, regional factors G_{rt}, and idiosyncratic components e_{yrnt}, follow stationary and normally distributed autoregressive processes. This assumption ensures the factors are stable over time and do not exhibit explosive behavior, allowing for meaningful economic interpretations.

A.2. Initialization and convergence criteria for MCMC

A.2.1. Initialization

The Markov Chain Monte Carlo (MCMC) estimation process begins with the initialization of the model parameters and factors:

- **Principal Component Analysis (PCA)**: PCA is used to obtain initial estimates of the common (world) factor F_t and the regional factors G_{rt}. The initial values of the factor loadings $\Lambda = (\Lambda_G, \Lambda_F)$ are also derived from PCA results. This step provides a reasonable starting point for the iterative MCMC process by capturing the major sources of variation in the data.
- **Setting Initial Values**: Initial values for the factors and parameters, including the variance matrices $\Psi = (\Psi_G, \Psi_F, \Psi_Y)$ and $\Sigma = (\Sigma_G, \Sigma_F, \Sigma_Y)$, are set based on the PCA-derived components and the residual variances. These initial values are crucial for ensuring the efficient convergence of the MCMC algorithm.

A.2.2. MCMC sampling procedure

The MCMC algorithm iteratively updates the model parameters and latent factors. The main steps are as follows:

- **Factor Sampling**: Given the current estimates of Λ, Ψ, Σ, and the observed data y_{rnt}, the algorithm samples the regional factors G_{rt} and subsequently the world factor F_t. This step involves sampling from the conditional posterior distributions of these factors.
- **Updating Factor Loadings and Variances**: With the newly sampled factors, the algorithm updates the factor loadings Λ, the dynamic parameters Ψ, and the variance parameters Σ. These updates are based on the current estimates of the factors, ensuring the model parameters adjust to the new factor estimates.
- **Iterative Process**: Steps 1 and 2 are repeated iteratively. The convergence of the MCMC chains is monitored to ensure the samples are representative of the posterior distribution of the model parameters.

A.2.3. Convergence criteria

To assess the convergence of the MCMC algorithm, we use the following criteria:

- **Burn-in Period**: The first 5000 iterations are discarded as the burn-in period. This phase allows the MCMC chains to reach the region of high posterior density, mitigating the influence of initial values on the final estimates.
- **Thinning**: After the burn-in period, every 50th sample is retained from the subsequent 5000 iterations. Thinning helps reduce the autocorrelation in the samples, providing a more independent set of draws for posterior inference.
- **Diagnostic Checks**: We employ convergence diagnostics, such as the Gelman-Rubin statistic, to ensure the chains have converged. An $\widehat{R}$ statistic close to 1.0 indicates that the chains have converged to the stationary distribution. Additionally, the effective sample size (ESS) is calculated to ensure the number of independent samples is adequate for reliable posterior analysis.

By adhering to these identification assumptions, initialization strategies, and convergence criteria, the DHFM provides robust estimates of the trade factors, capturing the complex structure of international trade dynamics at multiple levels.

Appendix B. Data

Table B.1
CN macro variables.

Indicators	Period	Speed	Change
Real Activities			
1. Value Added of Industry	2001/01–2023/06	Slow	None
2. VAI: Light Industry	2001/01–2013/08	Slow	None
3. VAI: Heavy Industry	2001/01–2013/08	Slow	None
4. Retail Sales of Consumer Goods	2001/01–2023/06	Slow	△ln
5. Industrial Sales Value: Delivery Value for Export	2001/01–2023/06	Slow	△ln
6. Industrial Sales Value: Delivery Value for Export: YoY	2001/01–2023/06	Slow	None
7. Energy Production: Electricity	2001/01–2023/06	Slow	△ln
8. Transport: Passenger Traffic	2001/01–2023/06	Slow	△ln
9. Automobile: Sales	2001/01–2023/06	Slow	△ln
10. Automobile: Sales: Domestic Made (DM)	2001/01–2023/06	Slow	△ln
11. Automobile: Production	2001/01–2023/06	Slow	△ln
12. Automobile: Production: Domestic Made (DM)	2001/01–2023/06	Slow	△ln
13. Steel Production: Iron Ore	2001/01–2022/12	Slow	△ln
14. Steel Production: Coke	2001/01–2023/06	Slow	△ln
15. Steel Production: Ferroalloy	2001/01–2022/12	Slow	△ln
16. Steel Production: Crude Steel	2001/01–2022/12	Slow	△ln
17. Steel Production: Steel Product (SP)	2001/01–2022/12	Slow	△ln
18. Petro Production: Crude Oil Processed	2001/01–2023/06	Slow	△ln
19. Petro Production: Crude Oil	2001/01–2023/06	Slow	△ln
20. Petro Production: Natural Gas	2001/01–2023/06	Slow	△ln
21. Petro Production: Oil Product: Gasoline	2001/01–2023/06	Slow	△ln
22. Petro Production: Oil Product: Coal Oil	2001/01–2023/06	Slow	△ln
23. Petro Production: Oil Product: Diesel Oil	2001/01–2023/06	Slow	△ln
24. Petro Production: Fuel Oil	2001/01–2023/06	Slow	△ln
25. Industrial Inventory: Finished Product	2001/01–2023/06	Slow	△ln
26. Purchasing Managers' Index: Manufacturing	2005/01–2023/06	Slow	None
27. PMI: Manufacturing: New Export Order	2005/01–2023/06	Slow	None
Investments			
28. Fixed Asset Investment	2001/01–2023/06	Slow	△ln
29. FDI: Utilized (not yet included all finance)	2001/01–2023/06	Slow	△ln

(*continued on next page*)

Table B.1 (*continued*)

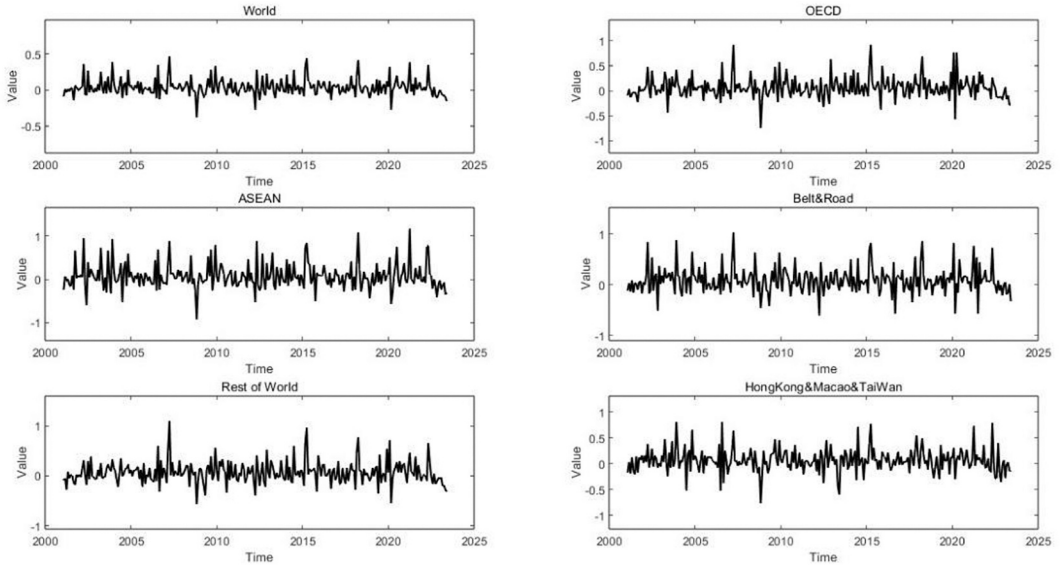
Indicators	Period	Speed	Change
30. FDI: Utilized (included all finance)	2001/01–2023/06	Slow	△ln
International Accounts			
31. Monetary Authority: Asset: Total	2002/01–2023/06	Fast	△ln
32. Monetary Authority: Asset: Foreign Asset	2001/01–2023/06	Fast	△ln
33. Monetary Authority: Asset: Foreign Asset: Foreign Exchange	2001/01–2023/06	Fast	△ln
34. Monetary Authority: Asset: Foreign Asset: Gold	2001/01–2023/06	Fast	△ln
35. Monetary Authority: Asset: Foreign Asset: Other	2001/01–2023/06	Fast	△ln
36. Monetary Authority: Liab: Reserve Money	2001/01–2023/06	Fast	△ln
37. Monetary Authority: Liab: Reserve Money: Currency Issue	2001/01–2023/06	Fast	△ln
38. Official Reserve Asset: Foreign Reserve(FR)	2001/01–2023/06	Fast	△ln
Exchange Rates and Swaps			
39. Foreign Exchange Rate: PBC: RMB to USD	2001/01–2023/06	Fast	None
40. Currency Swap: USD: 1 Week: Bid	2006/09–2023/06	Fast	None
41. Currency Swap: USD: 1 Week: Offer	2006/09–2023/06	Fast	None
42. Currency Swap: USD: 1 Month: Bid	2006/09–2023/06	Fast	None
43. Currency Swap: USD: 1 Month: Offer	2006/09–2023/06	Fast	None
44. Currency Swap: USD: 3 Month: Bid	2006/09–2023/06	Fast	None
45. Currency Swap: USD: 3 Month: Offer	2006/09–2023/06	Fast	None
46. Currency Swap: USD: 6 Month: Bid	2006/09–2023/06	Fast	None
47. Currency Swap: USD: 1 Year: Bid	2006/09–2023/06	Fast	None
48. Currency Swap: USD: 6 Month: Offer	2006/09–2023/06	Fast	None
49. Currency Swap: USD: 1 Year: Offer	2006/09–2023/06	Fast	None
Government			
50. Govt Revenue: General Public Budget Revenue	2001/01–2023/06	Slow	△ln
51. Govt Expenditure: General Public Budget Expenditure	2001/01–2023/06	Slow	△ln
52. Govt Revenue: General Public Budget Revenue: Tax	2001/01–2023/06	Slow	△ln
53. Govt Revenue: General Public Budget Revenue: Tax: Tariffs	2001/01–2023/06	Slow	△ln
54. Govt Revenue: General Public Budget Revenue: Tax: Value Added	2001/01–2023/06	Slow	△ln
55. Govt Revenue: General Public Budget Revenue: Tax: Stamp Duty: Securities Trading	2001/01–2023/06	Slow	△ln
56. Govt Revenue: General Public Budget Revenue: Tax: Enterprises Income	2001/01–2023/06	Slow	△ln
Money Supply and Credits			
57. Money Supply M0	2001/01–2023/06	Fast	△ln
58. Money Supply M1	2001/01–2023/06	Fast	△ln
59. Money Supply M1: Demand Deposit	2001/01–2023/06	Fast	△ln
60. Money Supply M2	2001/01–2023/06	Fast	△ln
61. Money Supply M2: Quasi Money: Saving Deposit	2001/01–2023/06	Fast	△ln
62. Money Supply M2: Quasi Money: Time Deposit	2001/01–2023/06	Fast	△ln
63. Money Supply M2: Quasi Money: Other Deposit	2001/01–2023/06	Fast	△ln
64. Loan	2001/01–2023/06	Slow	△ln
65. Required Reserve Ratio	2003/10–2023/06	Slow	None
Interest Rates			
66. Central Bank Benchmark Interest Rate: Loan to Financial Institutions: 3 Months	2001/01–2023/06	Slow	None
67. Central Bank Benchmark Interest Rate: Loan to Financial Institutions: 6 Months	2001/01–2023/06	Slow	None
68. Central Bank Benchmark Interest Rate: Loan to Financial Institutions: 1 Year	2001/01–2023/06	Slow	None
69. Central Bank Benchmark Interest Rate: Loan to Financial Institutions: 1 Month	2001/01–2023/06	Slow	None
70. Nominal Lending Rate: Within 1 Year (Including 1 Year)	2001/01–2023/06	Slow	None
71. Nominal Lending Rate: 1–5 Year (Including 5 Year)	2001/01–2023/06	Slow	None
72. Nominal Lending Rate: Over 5 Year	2001/01–2023/06	Slow	None
73. Nominal Lending Rate: Individual Housing Provident Fund Loan: 5 Year or Less	2001/01–2023/06	Slow	None
74. Nominal Lending Rate: Individual Housing Provident Fund Loan: Over 5 Year	2001/01–2023/06	Slow	None
75. Household Savings Deposits Rate: Demand	2001/01–2023/06	Slow	None
76. Household Savings Deposits Rate: Time: 3 Month	2001/01–2023/06	Slow	None
77. Household Savings Deposits Rate: Time: 6 Month	2001/01–2023/06	Slow	None
78. Household Savings Deposits Rate: Time: 1 Year	2001/01–2023/06	Slow	None
79. Household Savings Deposits Rate: Time: 2 Year	2001/01–2023/06	Slow	None
80. Household Savings Deposits Rate: Time: 3 Year	2001/01–2023/06	Slow	None
81. Shanghai Interbank Offered Rate (SHIBOR): Overnight	2006/10–2023/06	Fast	None
82. Shanghai Interbank Offered Rate (SHIBOR): 1 Month	2006/10–2023/06	Fast	None
83. Shanghai Interbank Offered Rate (SHIBOR): 3 Month	2006/10–2023/06	Fast	None
84. Shanghai Interbank Offered Rate (SHIBOR): 6 Month	2006/10–2023/06	Fast	None
85. Shanghai Interbank Offered Rate (SHIBOR): 1 Year	2006/10–2023/06	Fast	None
86. Wenzhou Index: Private Financing Composite Interest Rate: 1 Year	2013/01–2023/06	Fast	None
87. Wenzhou Index: Private Financing Composite Interest Rate	2012/10–2023/06	Fast	None
88. Bond Index: Interbank: Treasury Bond: Short Term	2002/06–2023/06	Fast	None
89. Bond Index: Interbank: Treasury Bond: Medium Term	2002/06–2023/06	Fast	None
90. Bond Index: Interbank: Treasury Bond: Long Term	2002/06–2023/06	Fast	None
91. Bond Index: Interbank: Policy Financial Bond	2002/06–2023/06	Fast	None
Stock Markets			
92. Index: Shanghai Stock Exchange: Composite	2001/01–2023/06	Fast	None

(*continued on next page*)

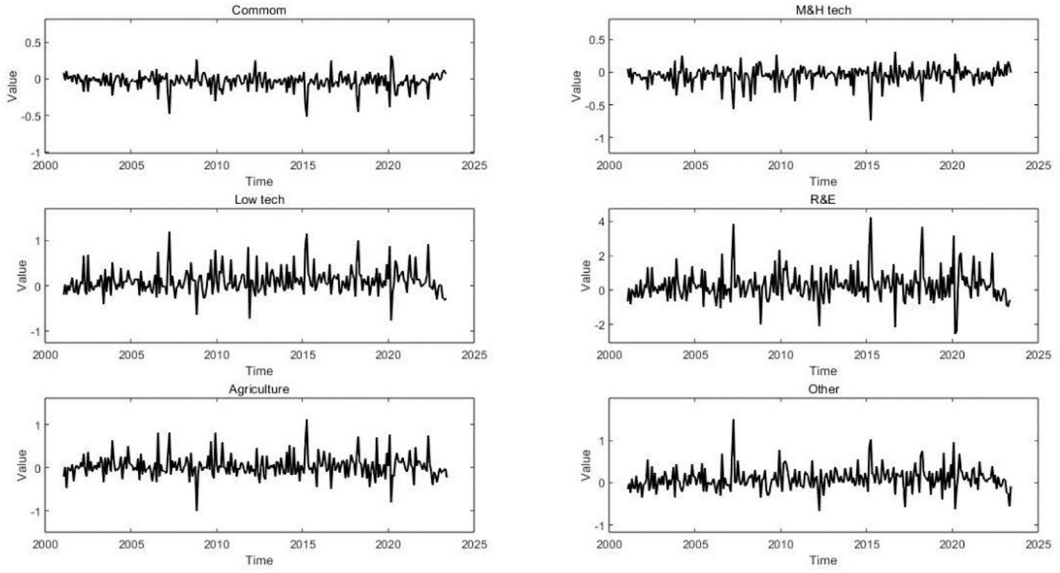
Table B.1 (*continued*)

Indicators	Period	Speed	Change
93. PE Ratio: Shanghai SE: All Share	2001/01–2023/06	Fast	None
94. PE Ratio: Shanghai SE: Financial	2001/04–2023/06	Fast	None
95. PE Ratio: Shanghai SE: Real Estate	2001/04–2023/06	Fast	None
96. PE Ratio: Shanghai SE: Construction	2001/04–2023/06	Fast	None
97. PE Ratio: Shanghai SE: Manufacturing	2001/04–2023/06	Fast	None
98. PE Ratio: Shenzhen SE: All Share	2001/01–2023/06	Fast	None
Price Indices			
99. Consumer Confidence Index	2001/01–2023/06	Fast	None
100. Consumer Price Index	2001/01–2023/06	Slow	△ln
101. CPI: Core (excl. Food&Energy)	2006/01–2023/06	Slow	△ln
102. CPI: non Food	2005/01–2023/06	Slow	△ln
103. CPI: Food, Tobacco&Liquor: Food	2001/01–2023/06	Slow	△ln
104. Settlement Price: Shanghai Future Exchange: Fuel Oil: First Month	2004/09–2023/06	Slow	△ln
105. Market Price: Monthly Avg: Oil Product: Diesel Oil, No 0	2004/08–2023/06	Slow	△ln
106. Retail Price: 36 City Avg: Fresh Pork: Refine Muscle	2001/01–2023/06	Slow	△ln
107. Producer Price Index(PPI)	2001/01–2023/06	Slow	△ln
108. Transaction Price: 36 City Avg: Round Steel: 18 mm, Q235	2001/01–2023/06	Slow	△ln
Employment			
109. No of Employee: Coal Mining&Dressing	2001/01–2023/06	Slow	△ln
110. No of Employee: Petroleum&Natural Gas Acquisition	2001/01–2023/06	Slow	△ln
111. No of Employee: Ferrous Metal Mining&Dressing	2001/01–2023/06	Slow	△ln
112. No of Employee: Food Manufacturing	2001/01–2023/06	Slow	△ln
113. No of Employee: Agricultural&Sideline Food Processing	2001/01–2023/06	Slow	△ln
114. No of Employee: Wine, Beverage&Refined Tea Manufacturing	2001/01–2023/06	Slow	△ln
115. No of Employee: Textile	2001/01–2023/06	Slow	△ln
116. No of Employee: Paper Making&Paper Product	2001/01–2023/06	Slow	△ln
117. No of Employee: Chemical Material&Product	2001/01–2023/06	Slow	△ln
118. No of Employee: Medical&Pharmaceutical Product	2001/01–2023/06	Slow	△ln
119. No of Employee: Electrical Machinery&Equipment	2001/01–2023/06	Slow	△ln
120. No of Employee: Computer, Communication&Other Electronic Equipment	2001/01–2023/06	Slow	△ln
Real Estate			
121. Floor Space Started: Commodity Bldg (CB)	2001/01–2023/06	Slow	None
122. Real Estate Inv: Source of Fund	2001/01–2023/06	Slow	None
123. Real Estate Inv: Source of Fund: Domestic Loan	2001/01–2023/06	Slow	None
124. Real Estate Inv: Source of Fund: Foreign Inv	2001/01–2023/06	Slow	None
125. Real Estate Inv: Source of Fund: Self Raised	2001/01–2023/06	Slow	None
126. Real Estate Inv: Source of Fund: Other	2001/01–2023/06	Slow	None
127. Building Sold	2001/01–2023/06	Slow	None
128. Building Sold: Residential	2001/01–2023/06	Slow	None
129. Real Estate Climate Index	2016/02–2023/06	Slow	None
130. Commodity Bldg Selling Price	2001/01–2023/06	Fast	△ln
131. Commodity Bldg Selling Price: Residential	2001/01–2023/06	Fast	△ln

Appendix C. Additional figures



(a) Regional Factors



(b) Industry Factors

Fig. C.1. Plots showing the factors extracted for different regions and industries.

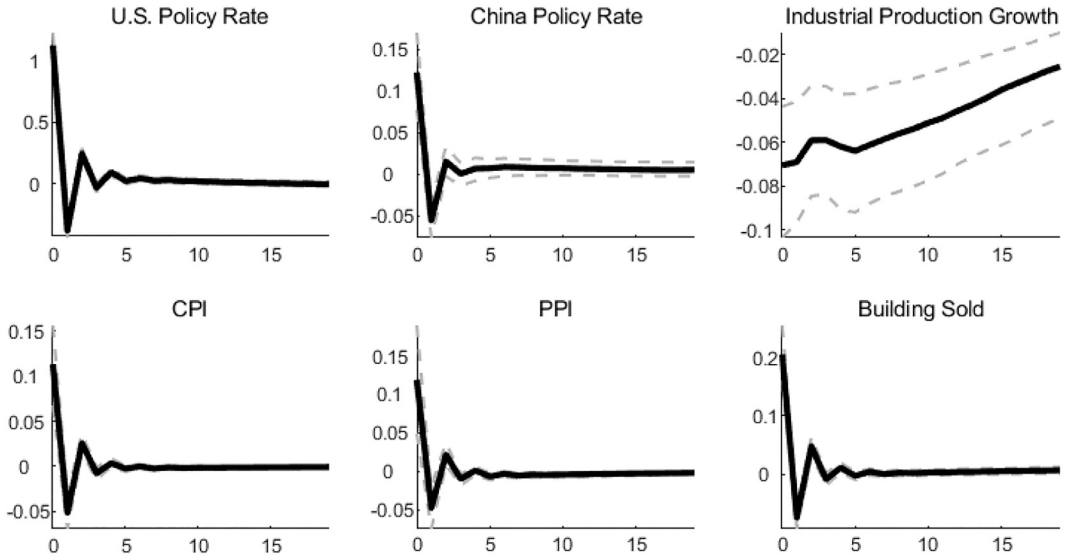


Fig. C.2. Impulse responses to the OECD factor (I).
Notes: Impulse responses to an OECD shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

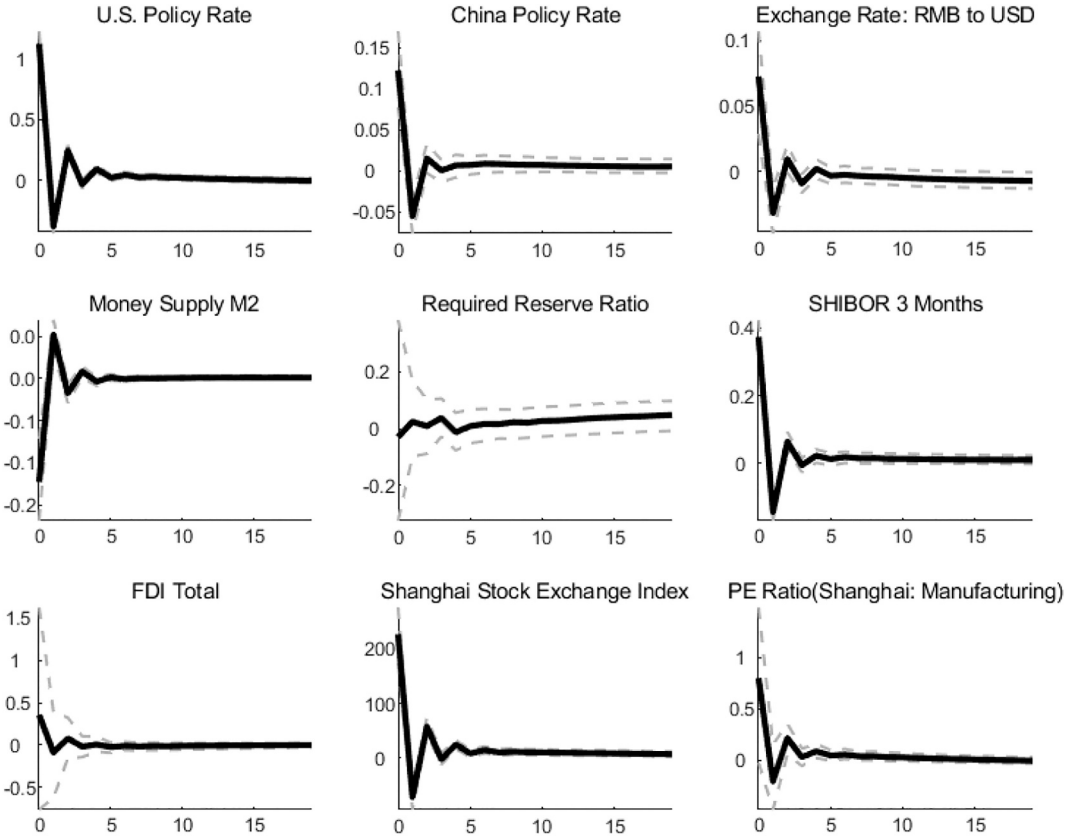


Fig. C.3. Impulse responses to the OECD Factor (II).
Notes: Impulse responses to an OECD shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

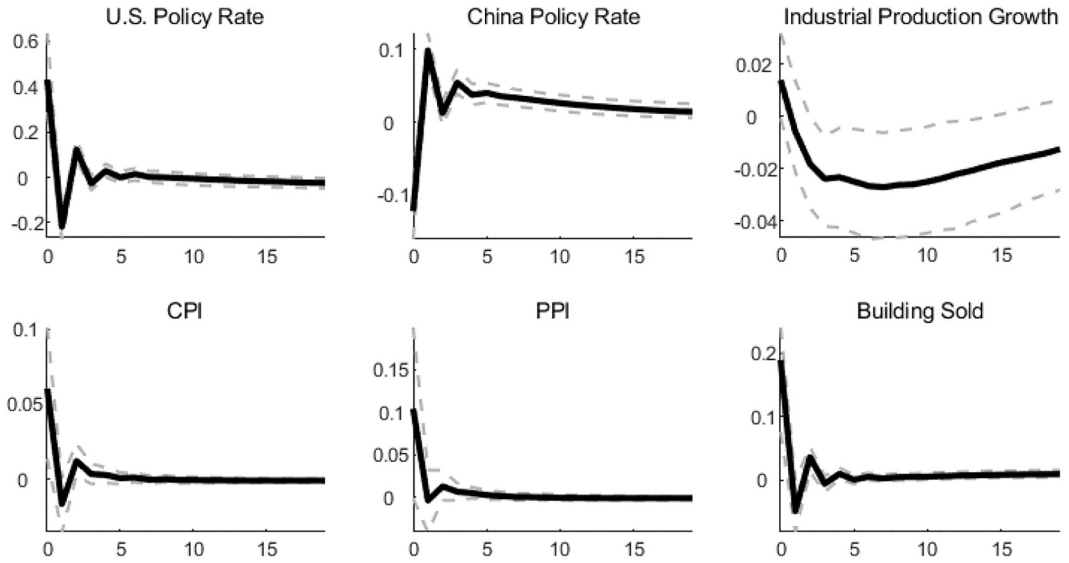


Fig. C.4. Impulse responses to the ASEAN factor (I).
Notes: Impulse responses to an ASEAN shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

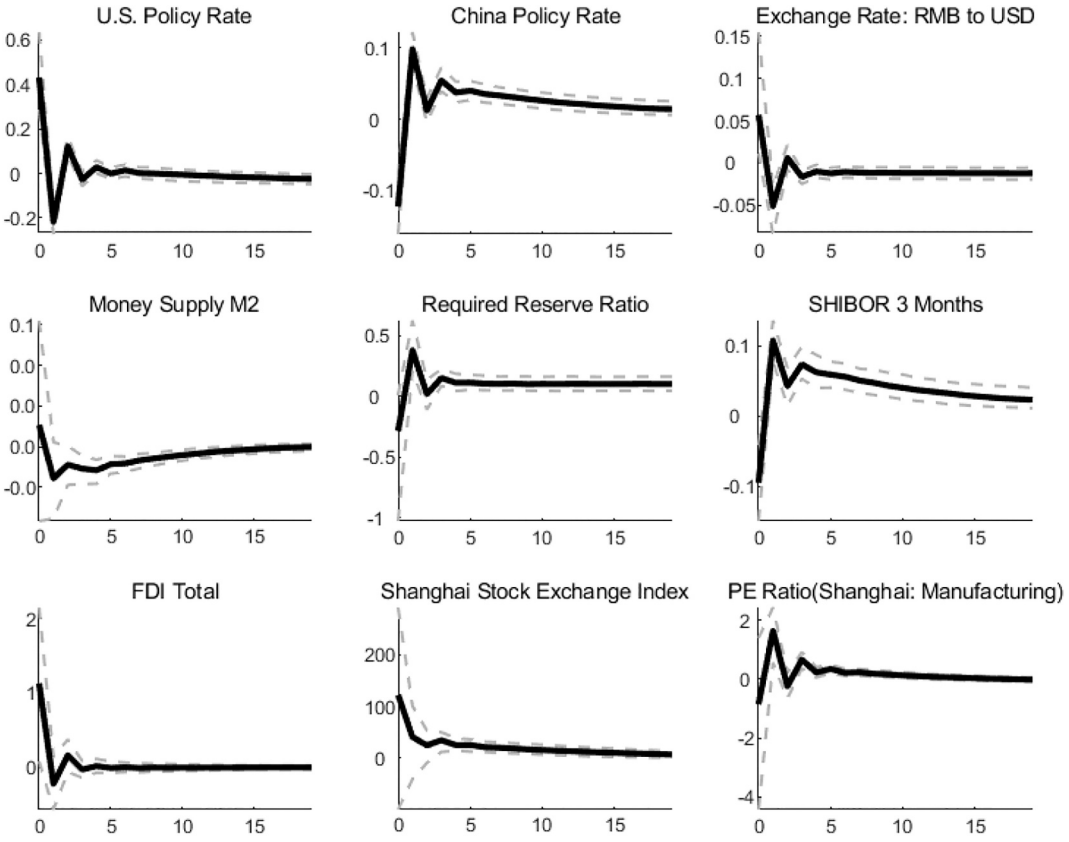


Fig. C.5. Impulse responses to the ASEAN factor (II).
Notes: Impulse responses to an ASEAN shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

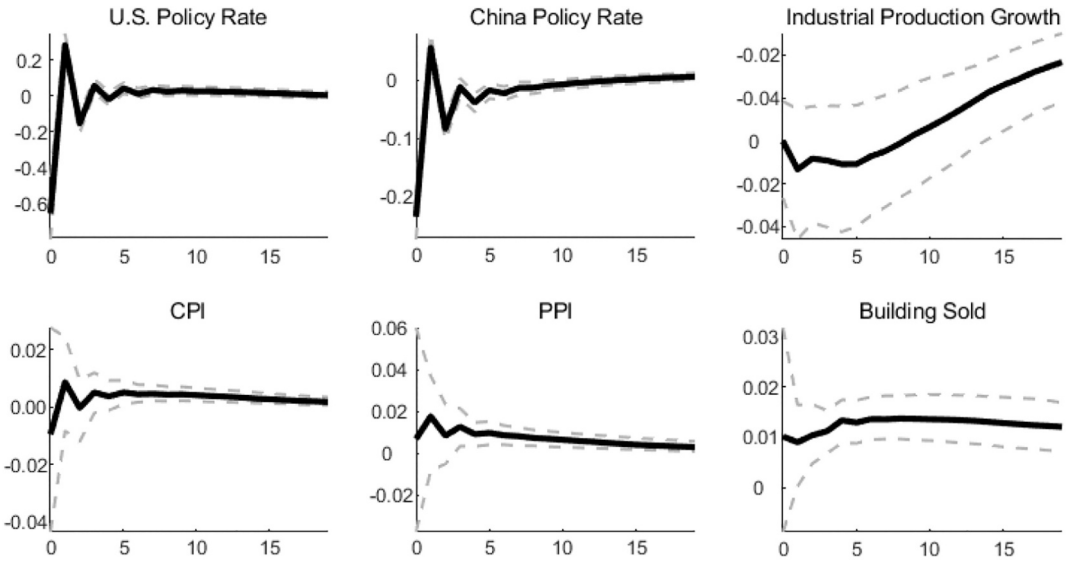


Fig. C.6. Impulse responses to the M&H-Tech factor (I).
Notes: Impulse responses to an M&H-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

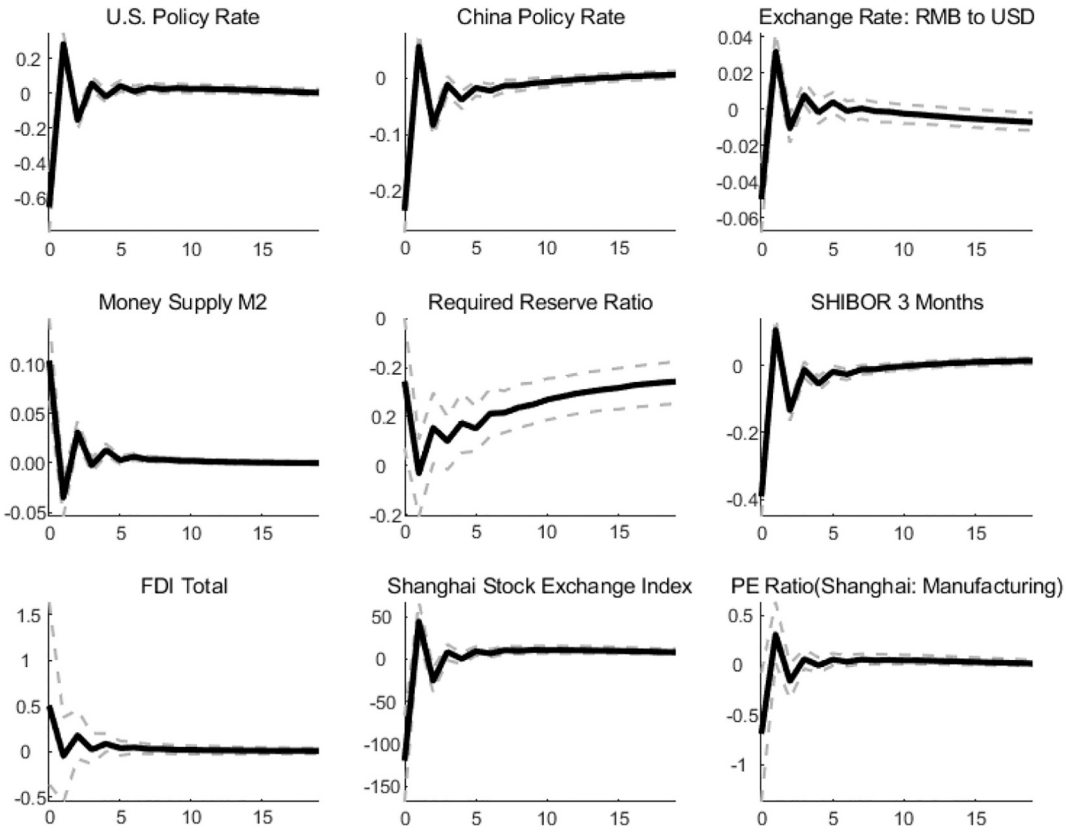


Fig. C.7. Impulse responses to the M&H-Tech factor (II).
Notes: Impulse responses to an M&H-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

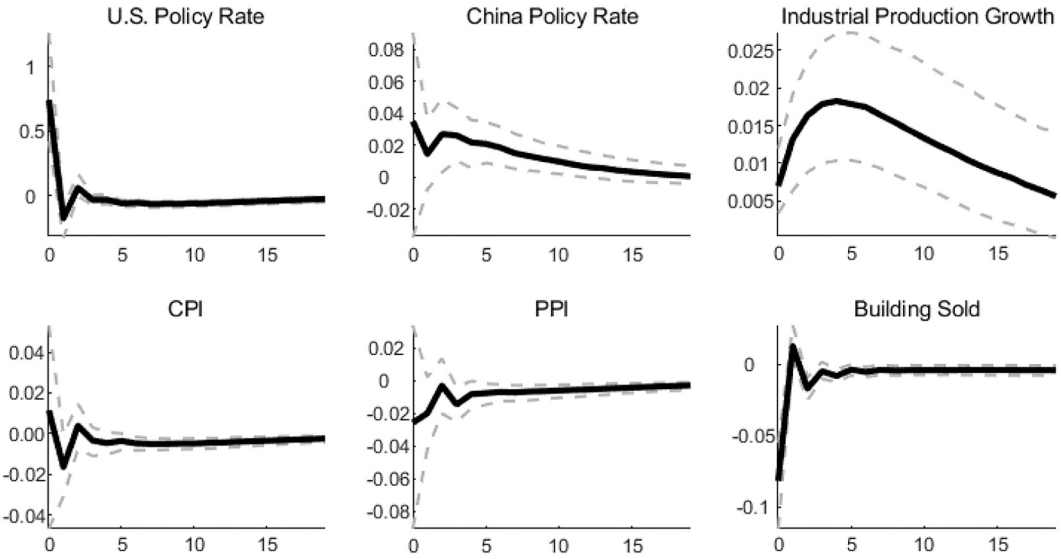


Fig. C.8. Impulse responses to the low-tech factor (I).
Notes: Impulse responses to a low-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

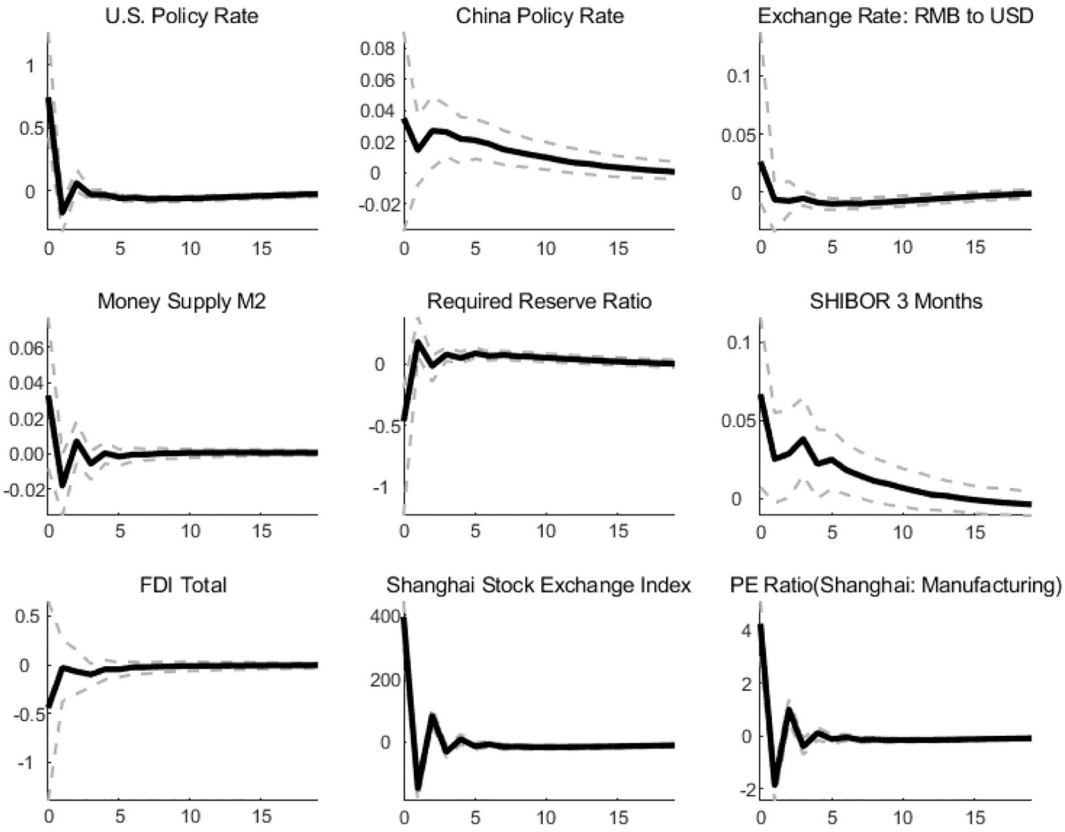


Fig. C.9. Impulse responses to the low-tech factor (II).
Notes: Impulse responses to a low-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

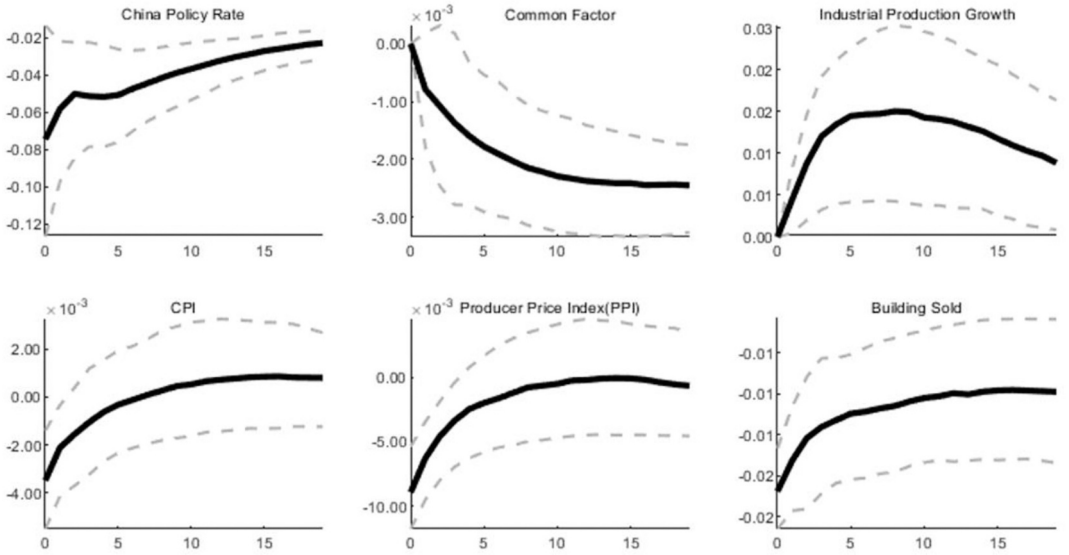


Fig. C.10. Impulse responses to a US monetary policy shock with industrial common factor (I).
Notes: Impulse responses to a US monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

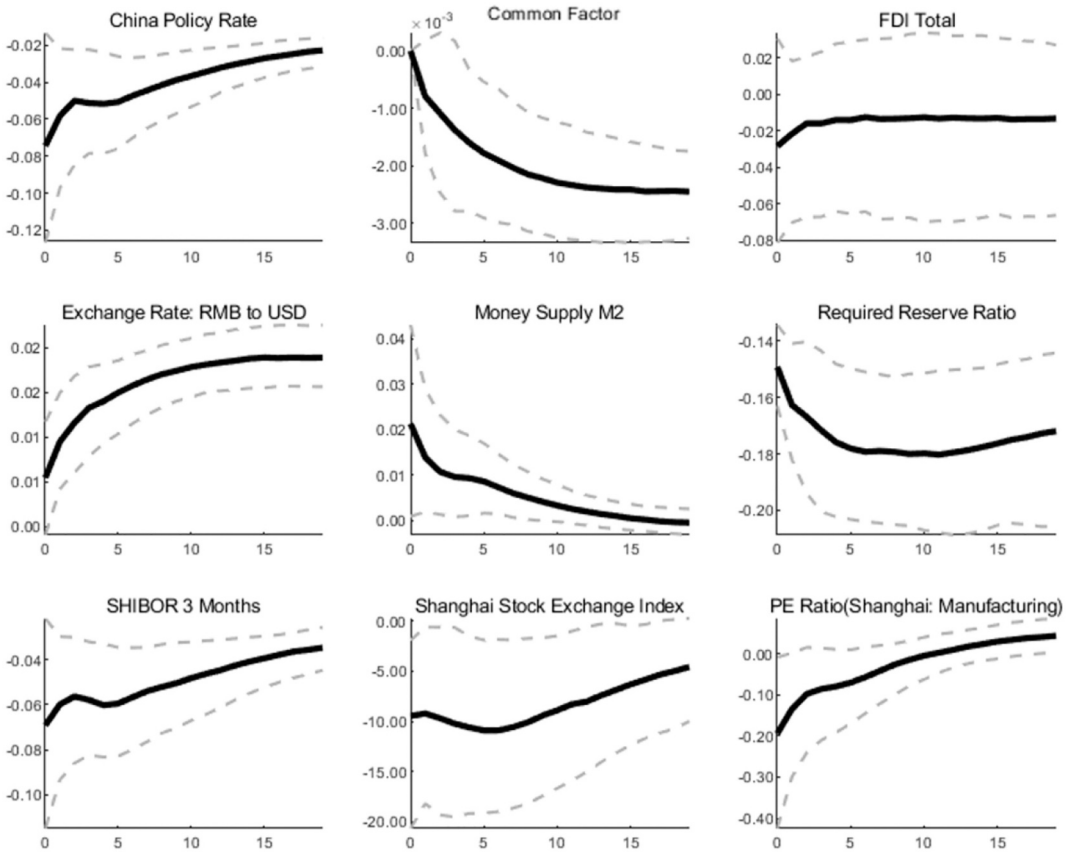


Fig. C.11. Impulse responses to a US monetary policy shock with industrial common factor (II).
Notes: Impulse responses to a US monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

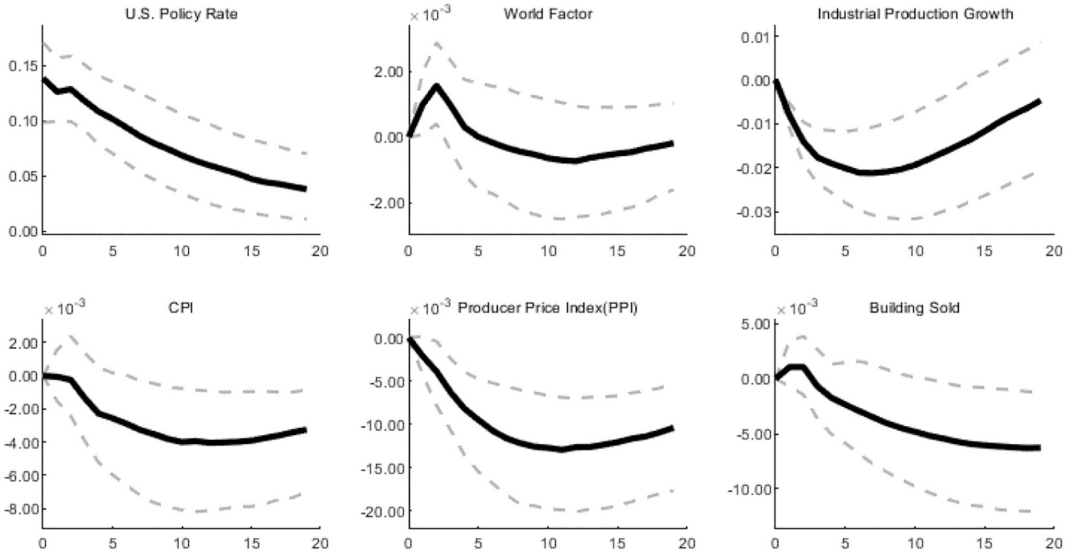


Fig. C.12. Impulse responses to a CN monetary policy shock with world factor (I).
Notes: Impulse responses to a CN monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

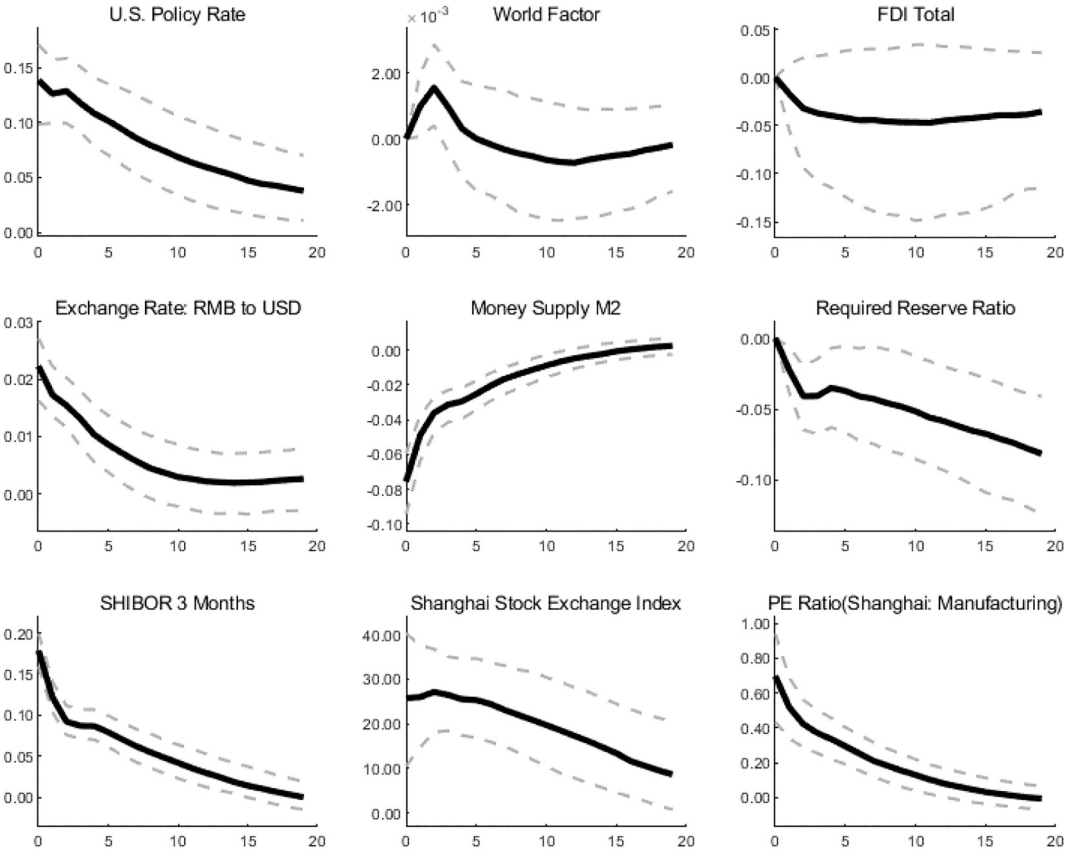


Fig. C.13. Impulse responses to a CN monetary policy shock with world factor (II).
Notes: Impulse responses to a CN monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

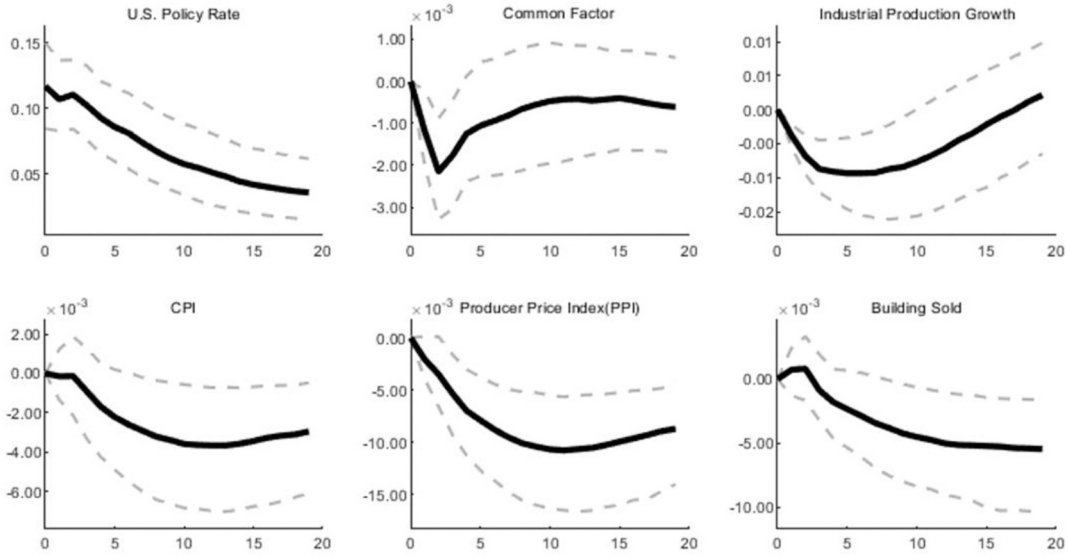


Fig. C.14. Impulse responses to a CN monetary policy shock with industrial common factor (III).
Notes: Impulse responses to a CN monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

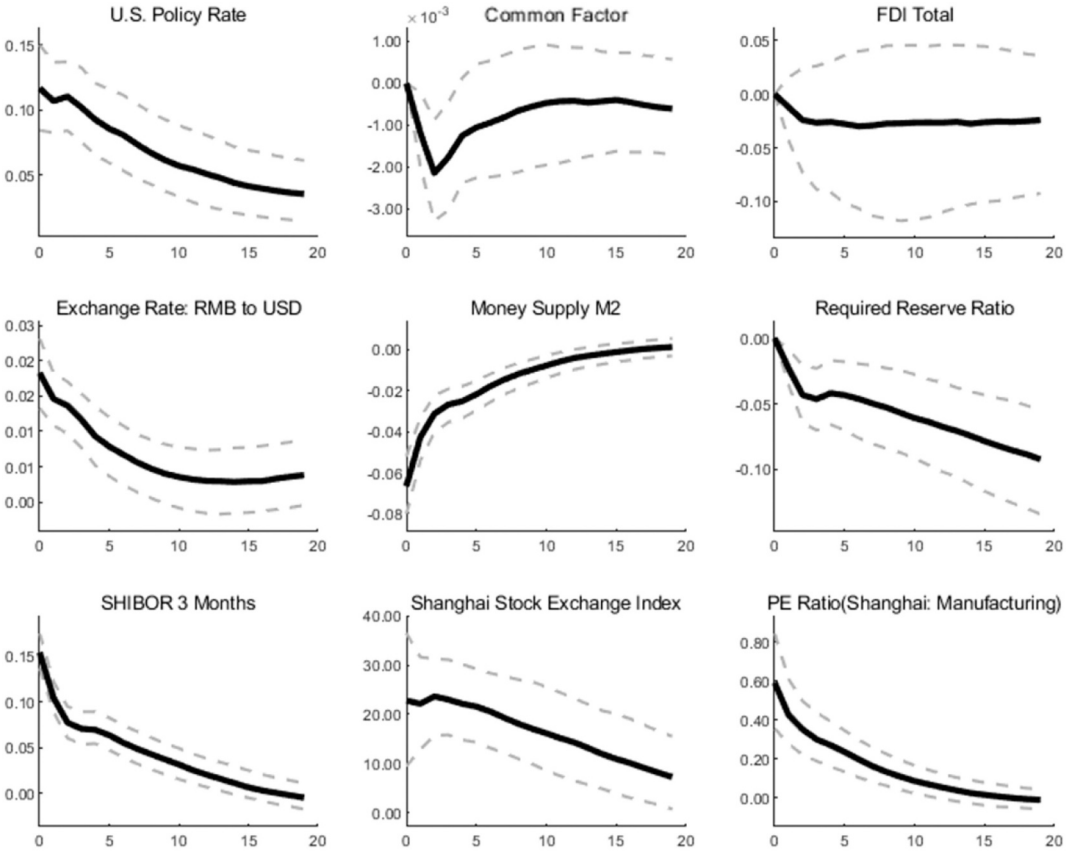


Fig. C.15. Impulse responses to a CN monetary policy shock with industrial common factor (IV).
Notes: Impulse responses to a CN monetary policy shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

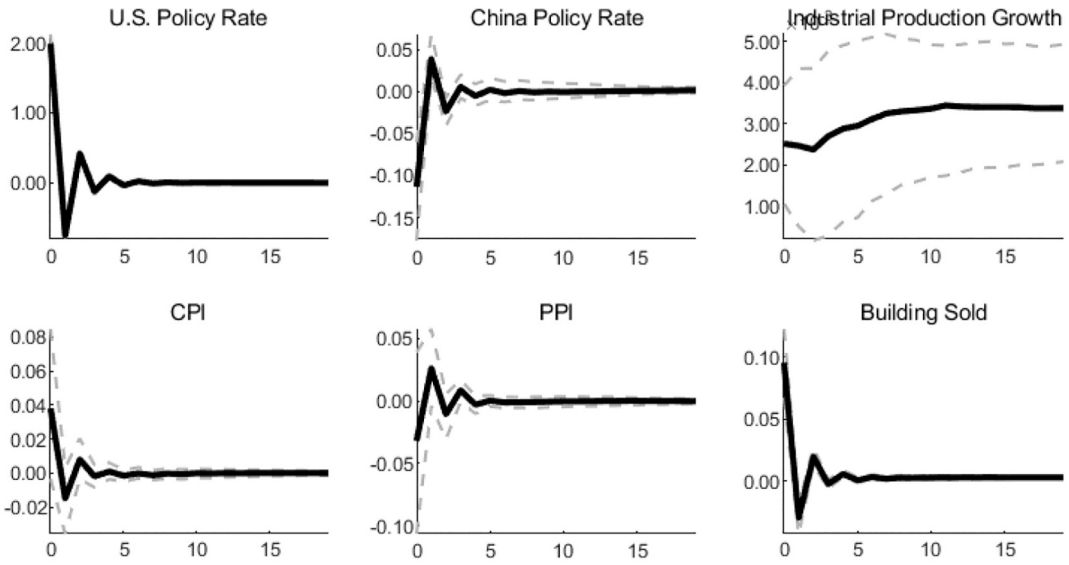


Fig. C.16. Impulse responses to the OECD factor (before the US-China trade war)(I).
Notes: Impulse responses to the OECD factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

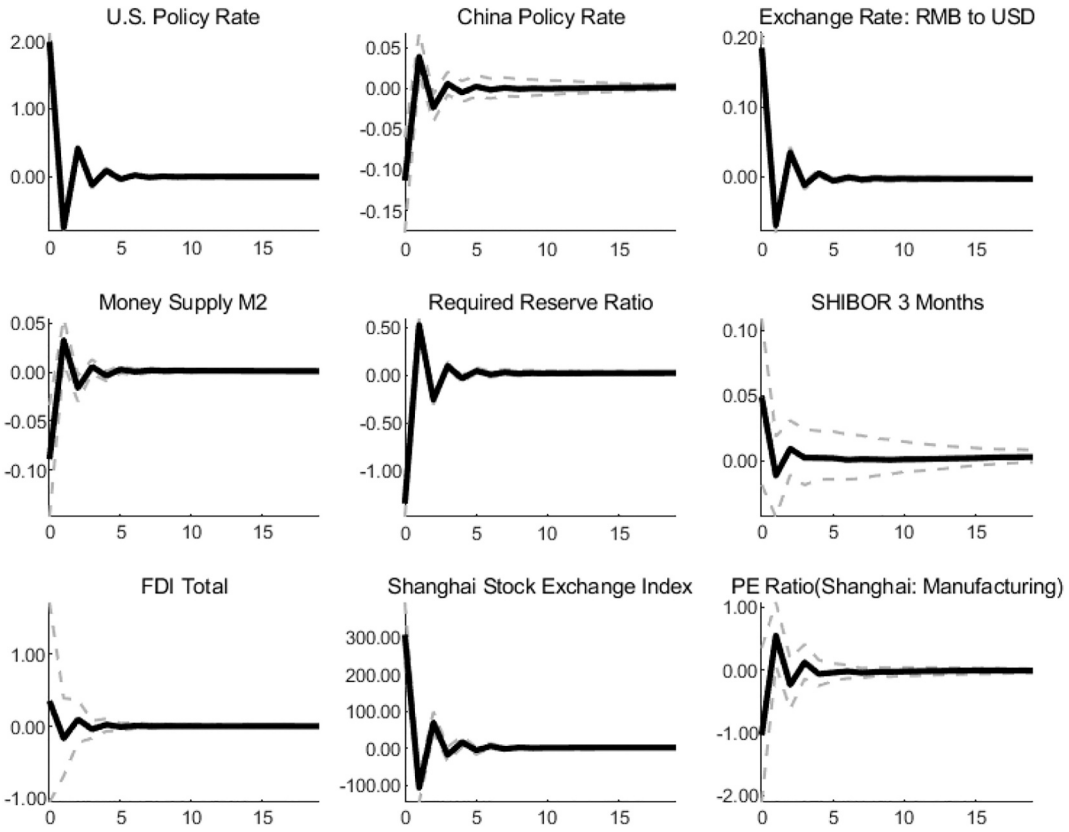


Fig. C.17. Impulse responses to the OECD factor (before the US-China trade war)(II).
Notes: Impulse responses to the OECD factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

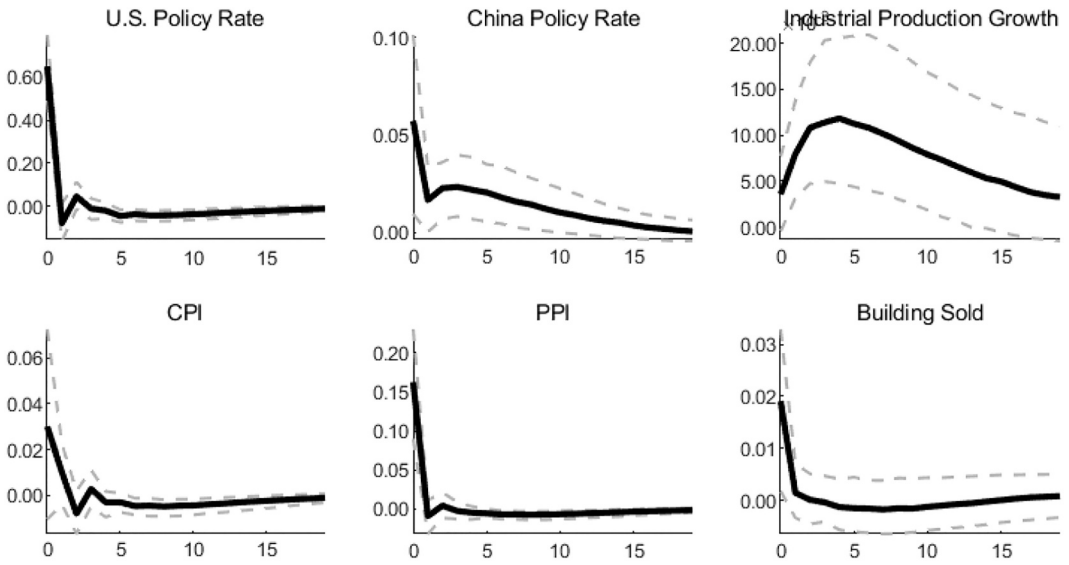


Fig. C.18. Impulse responses to the ASEAN factor (before the US-China trade war)(I).
Notes: Impulse responses to the ASEAN factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

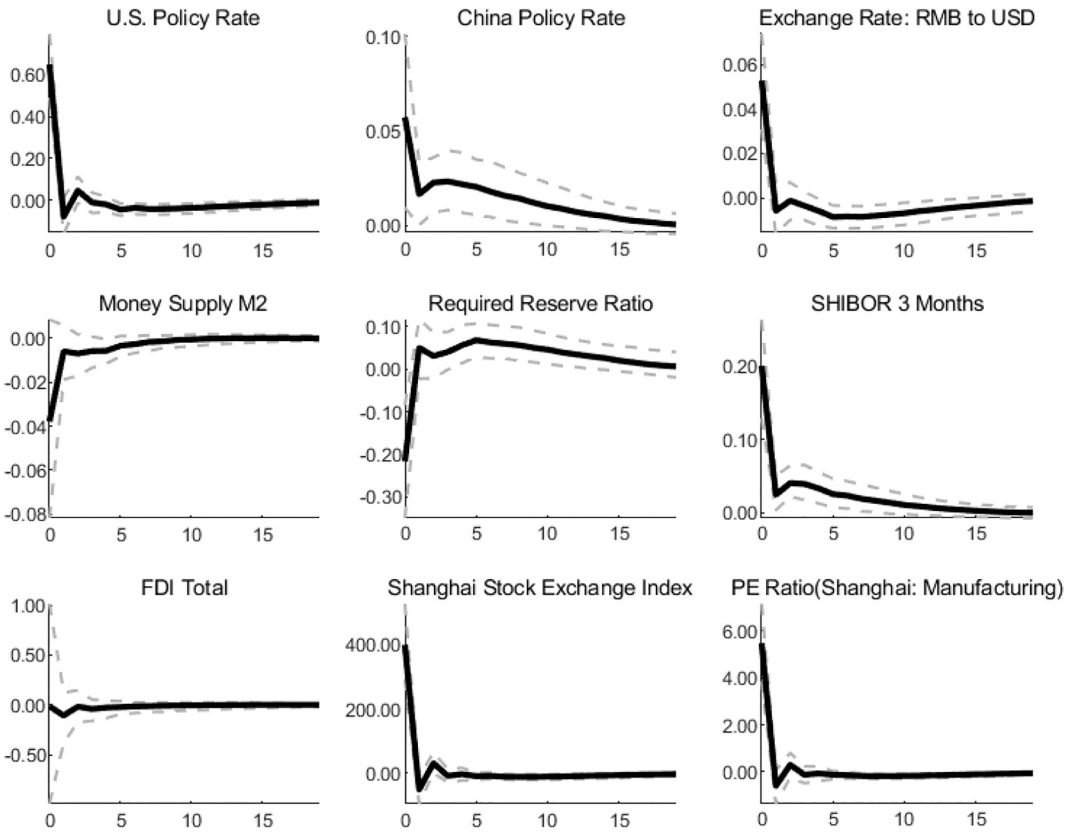


Fig. C.19. Impulse responses to the ASEAN factor (before the US-China trade war)(II).
Notes: Impulse responses to the ASEAN factor of key macroeconomic variables. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

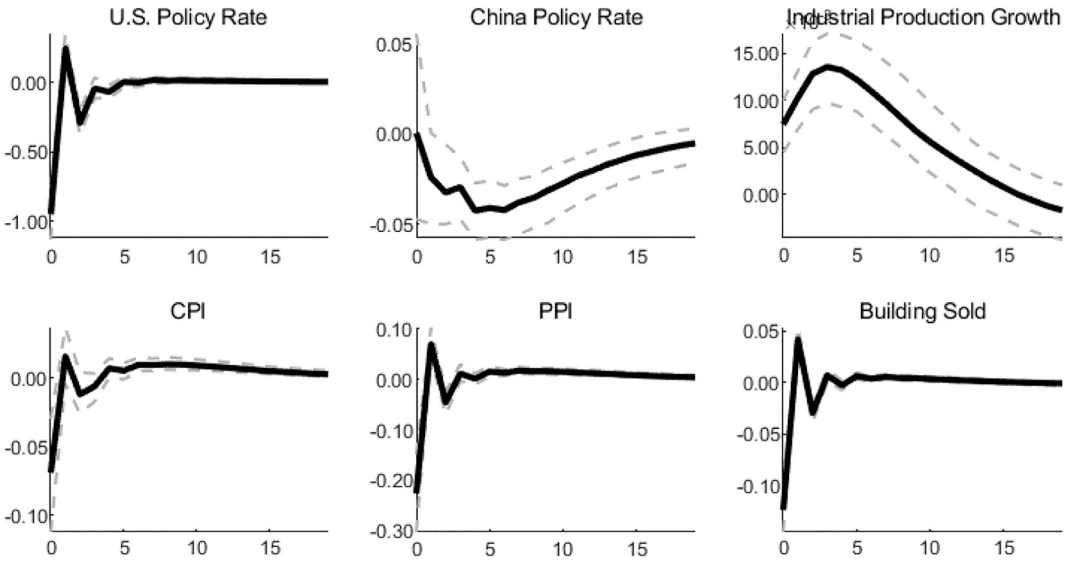


Fig. C.20. Impulse responses to the M&H-Tech factor (before the US-China trade war) (I).
Notes: Impulse responses to an M&H-tech shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

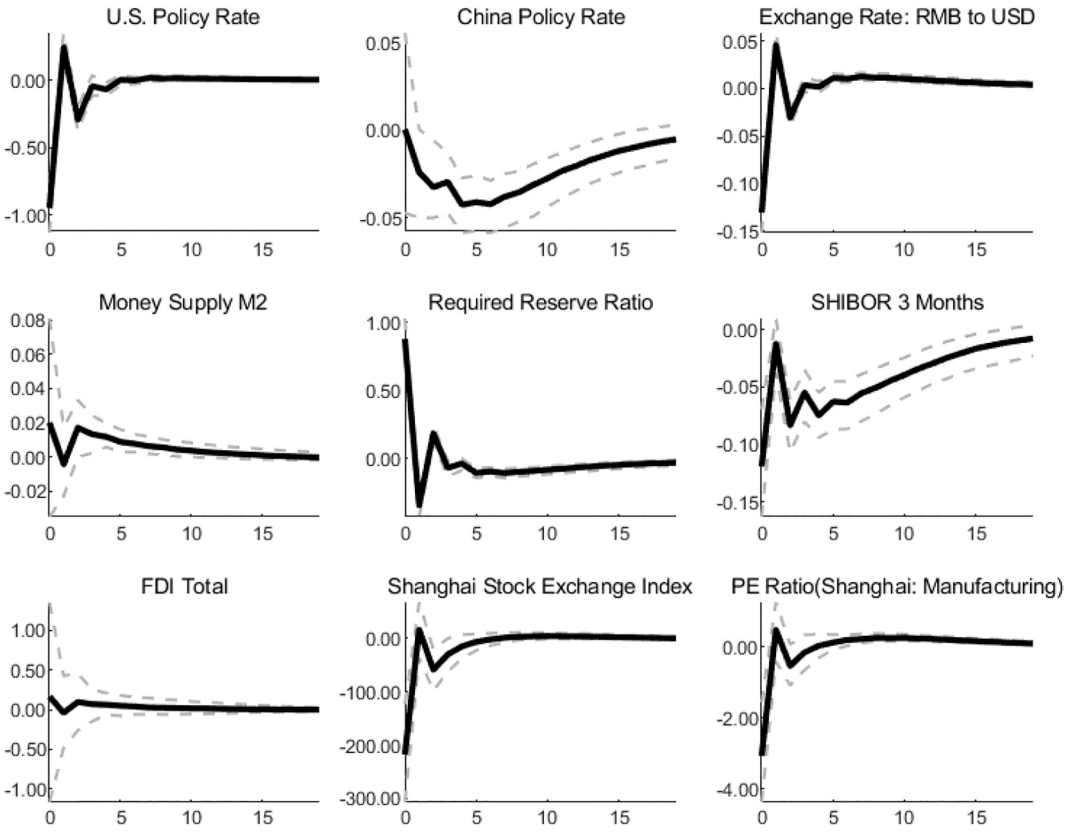


Fig. C.21. Impulse responses to the M&H-Tech factor (before the US-China trade war) (II).
Notes: Impulse responses to an M&H-tech shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

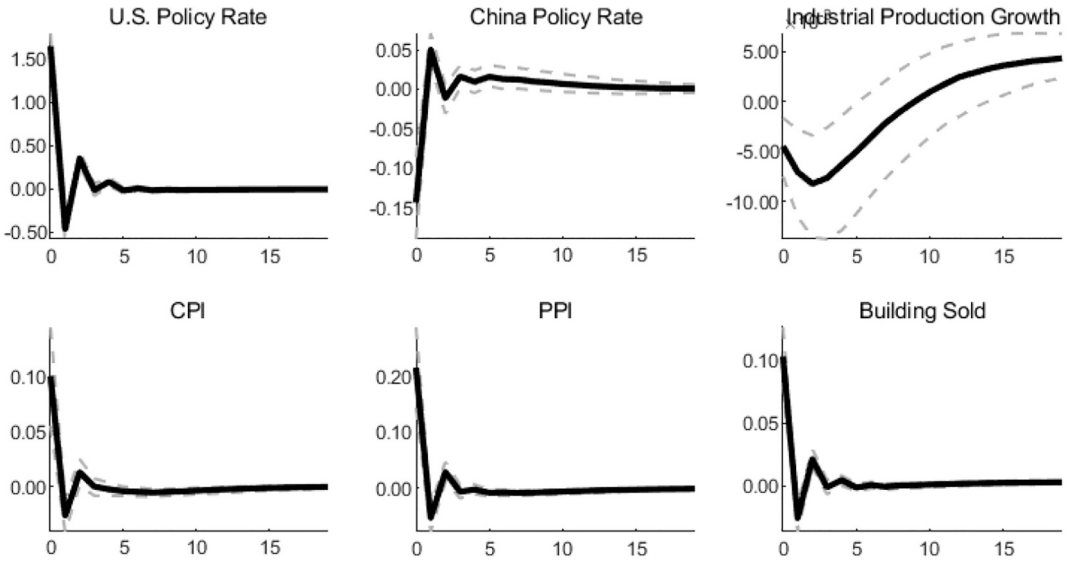


Fig. C.22. Impulse responses to the low-tech factor (before the US-China trade war) (I).
Notes: Impulse responses to a low-tech shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

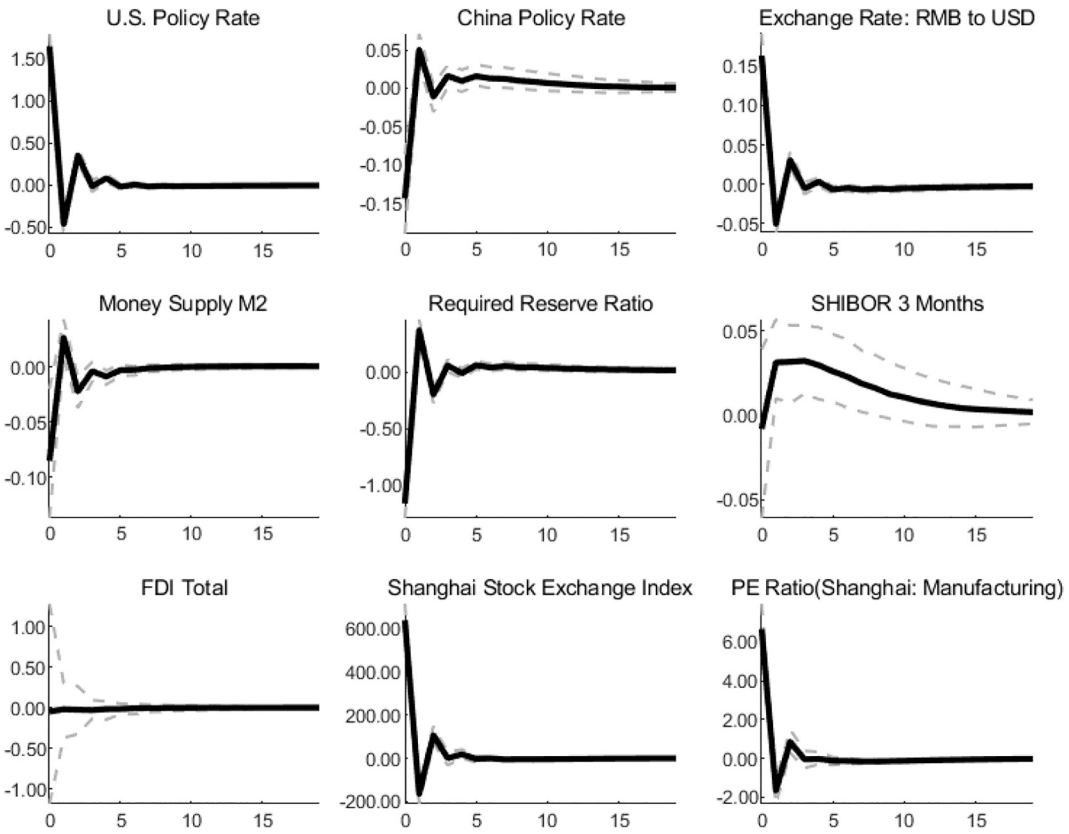


Fig. C.23. Impulse responses to the low-tech factor (before the US-China trade war) (II).
Notes: Impulse responses to a low-tech shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

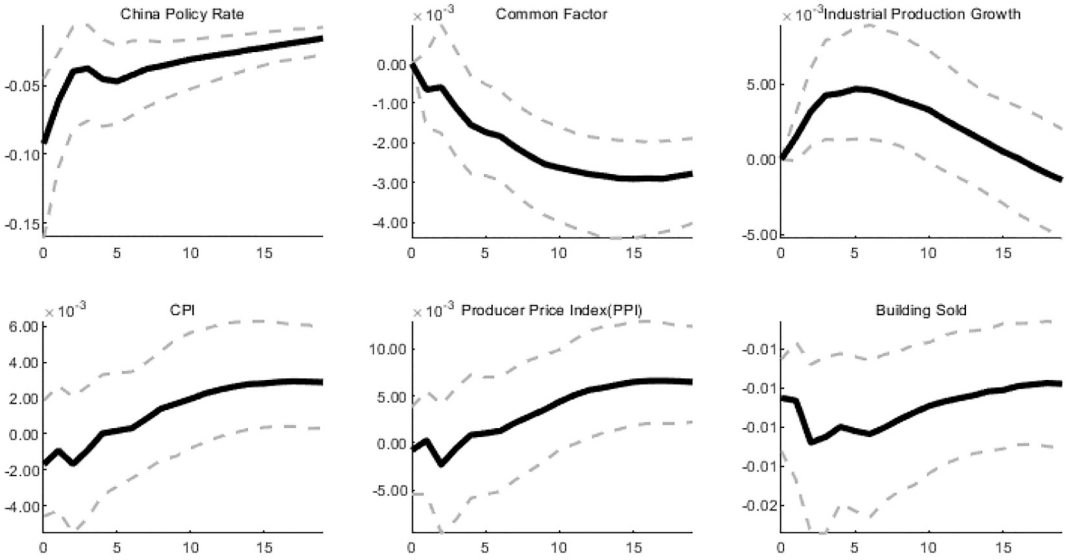


Fig. C.24. Impulse responses to a US monetary policy shock with industrial common factor (before the US-China trade war) (I).
Notes: Impulse responses to a US monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

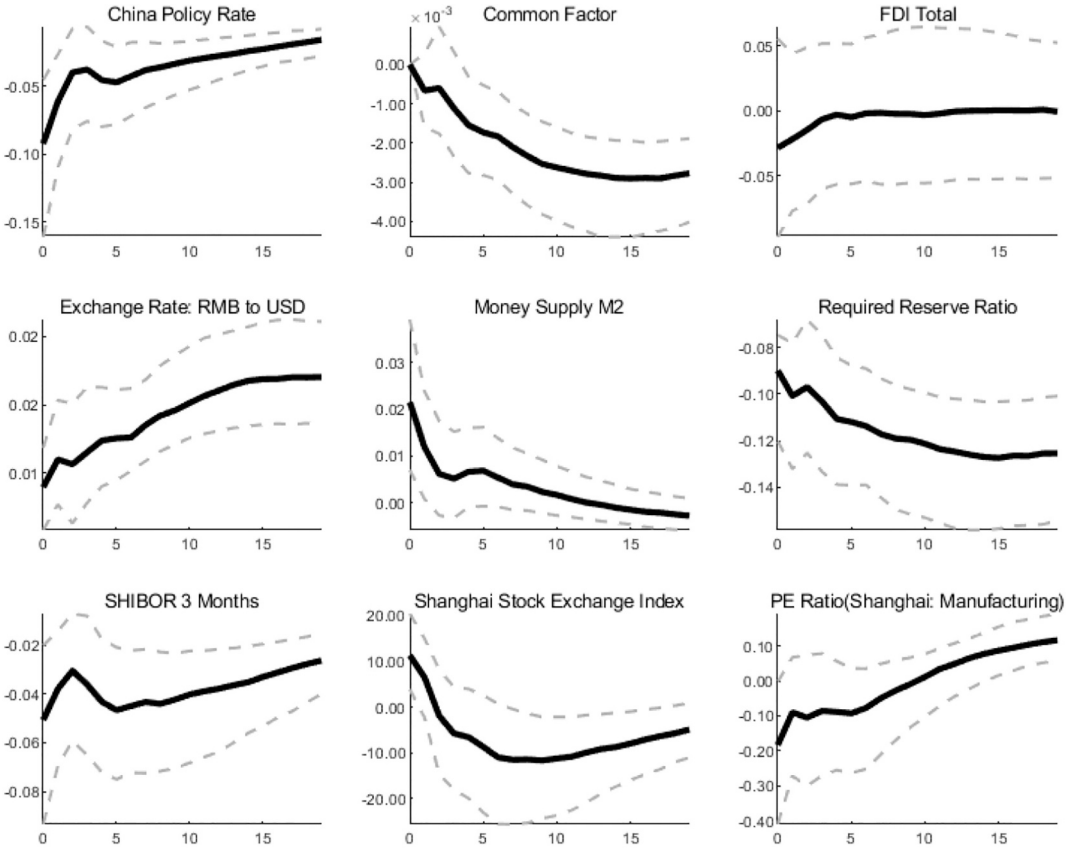


Fig. C.25. Impulse responses to a US monetary policy shock with industrial common factor (before the US-China trade war) (II).
Notes: Impulse responses to a US monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

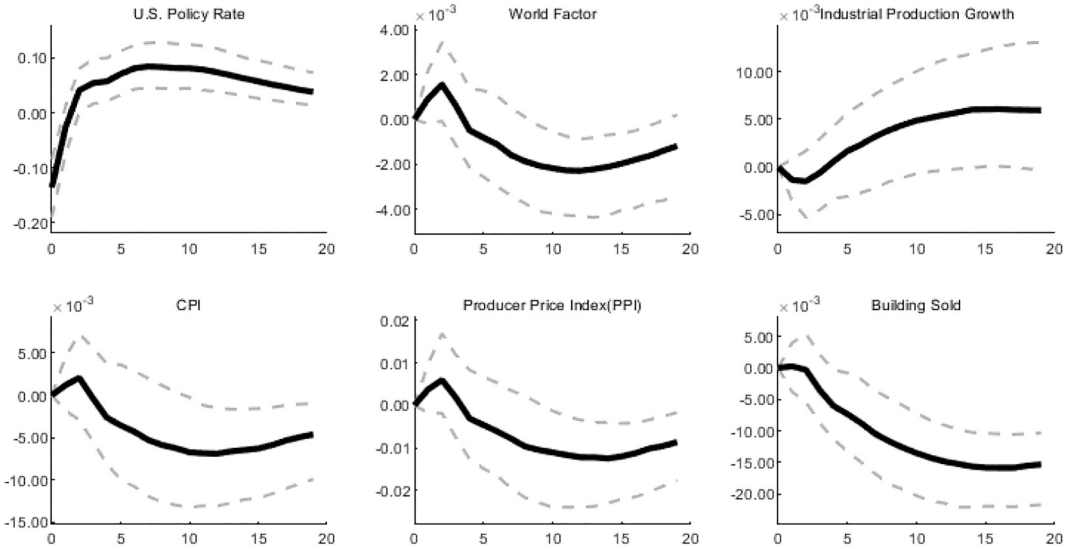


Fig. C.26. Impulse responses to a CN monetary policy shock with world factor (before the US-China trade war) (I).
Notes: Impulse responses to a CN monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

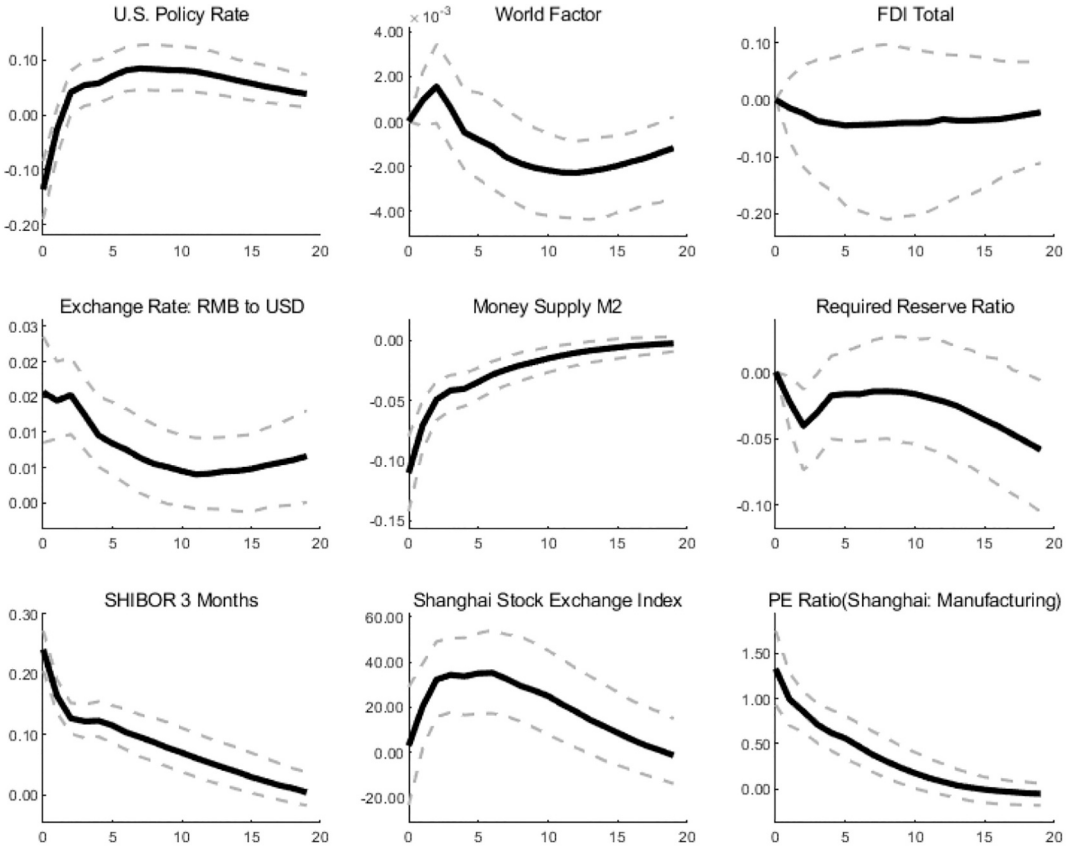


Fig. C.27. Impulse responses to a CN monetary policy shock with world factor (before the US-China trade war) (II).
Notes: Impulse responses to a CN monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

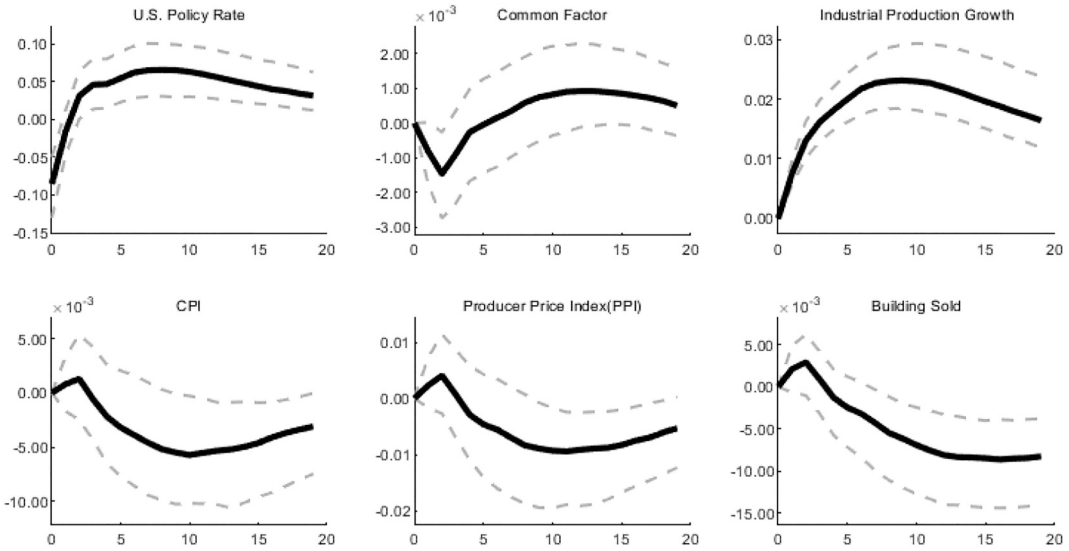


Fig. C.28. Impulse responses to a CN monetary policy shock with industrial common factor (before the US-China trade war) (III).
Notes: Impulse responses to a CN monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

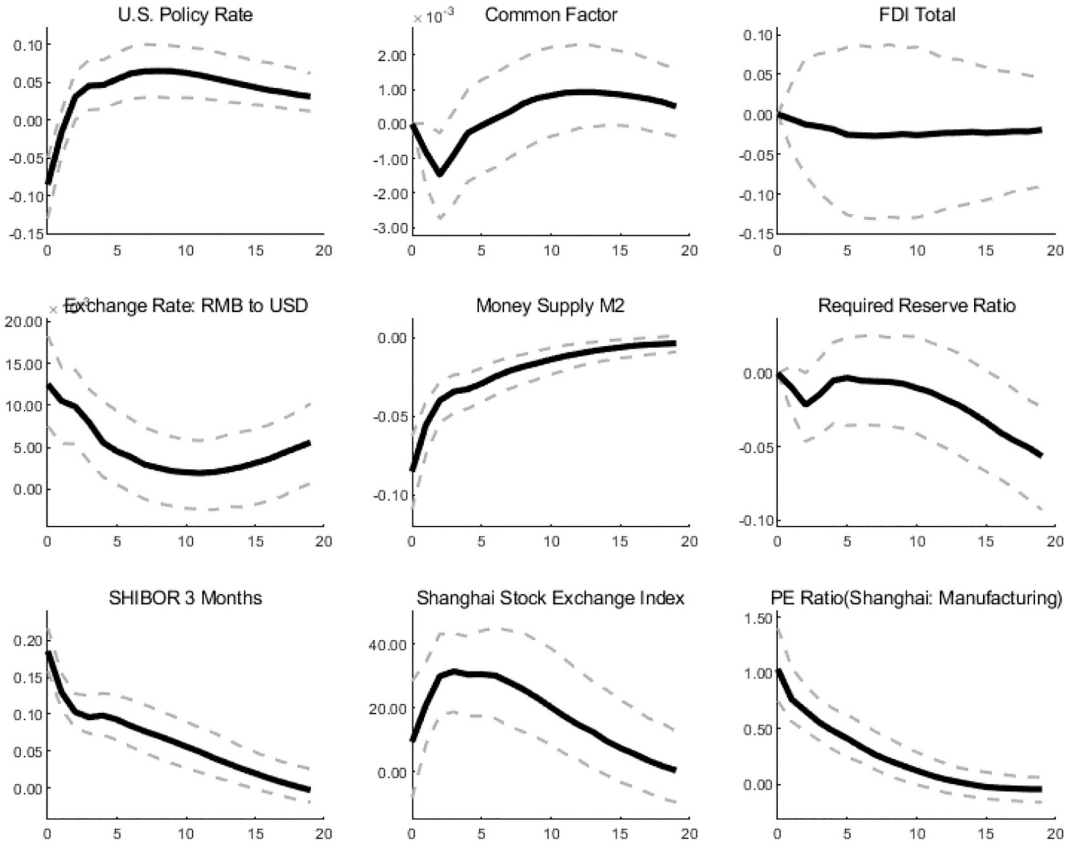


Fig. C.29. Impulse responses to a CN monetary policy shock with industrial common factor (before the US-China trade war) (IV).
Notes: Impulse responses to a CN monetary policy shock estimated using data from January 2001 to February 2018. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

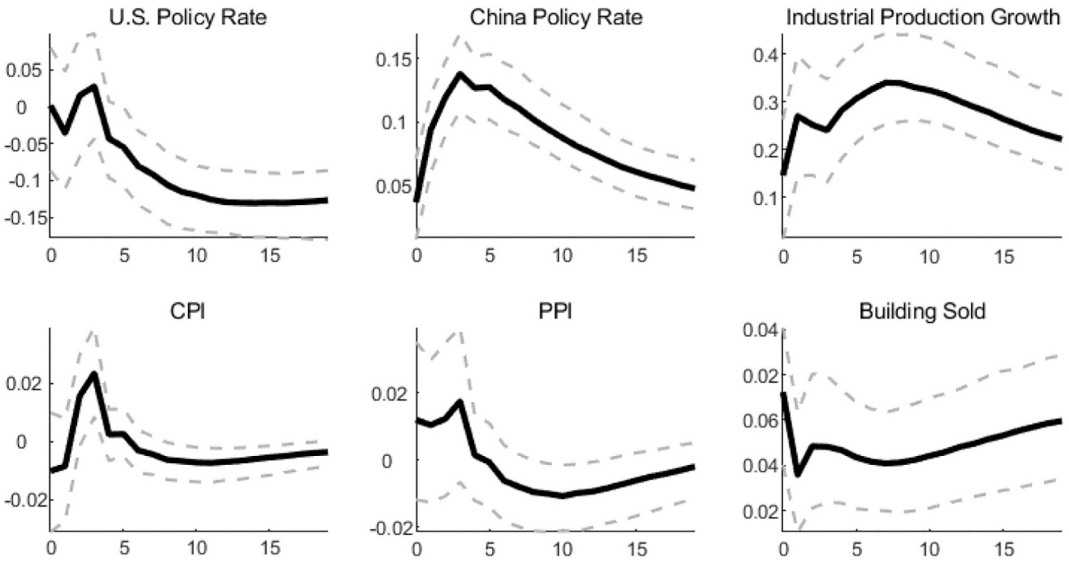


Fig. C.30. Impulse responses to the OECD factor (alternative order) (I).
Notes: Impulse responses to an OECD shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

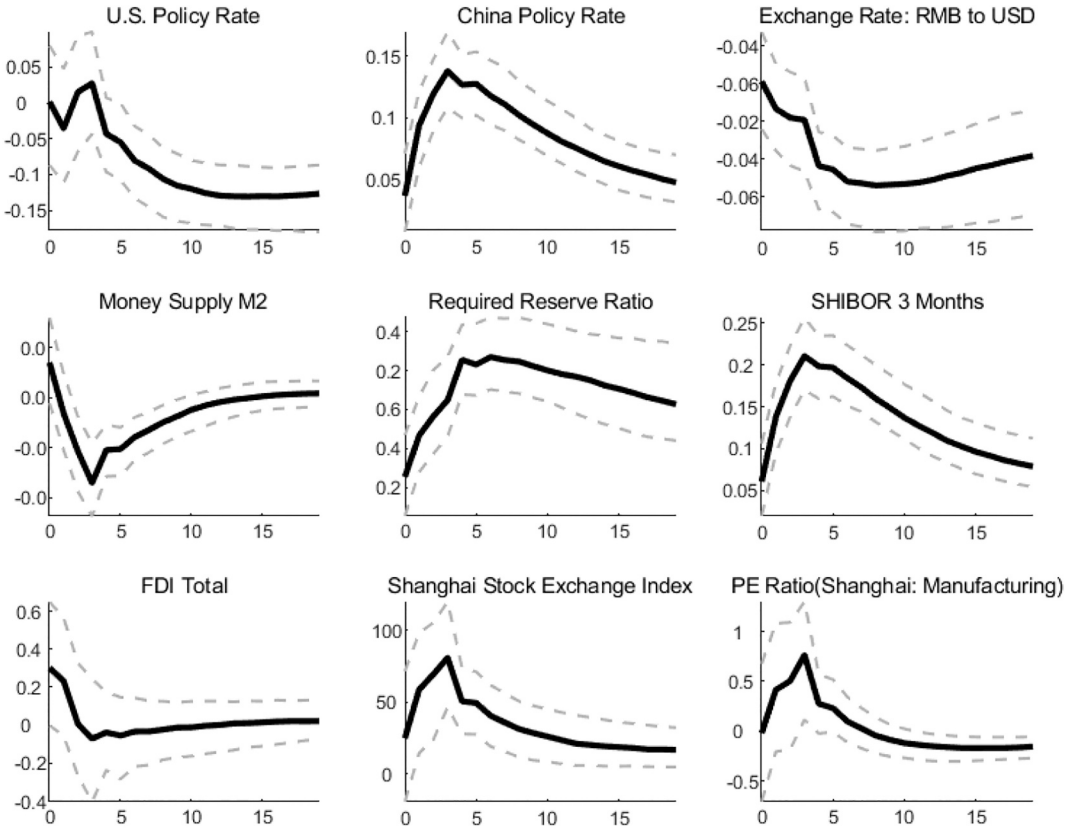


Fig. C.31. Impulse responses to the OECD factor (alternative order) (II).
Notes: Impulse responses to an OECD shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

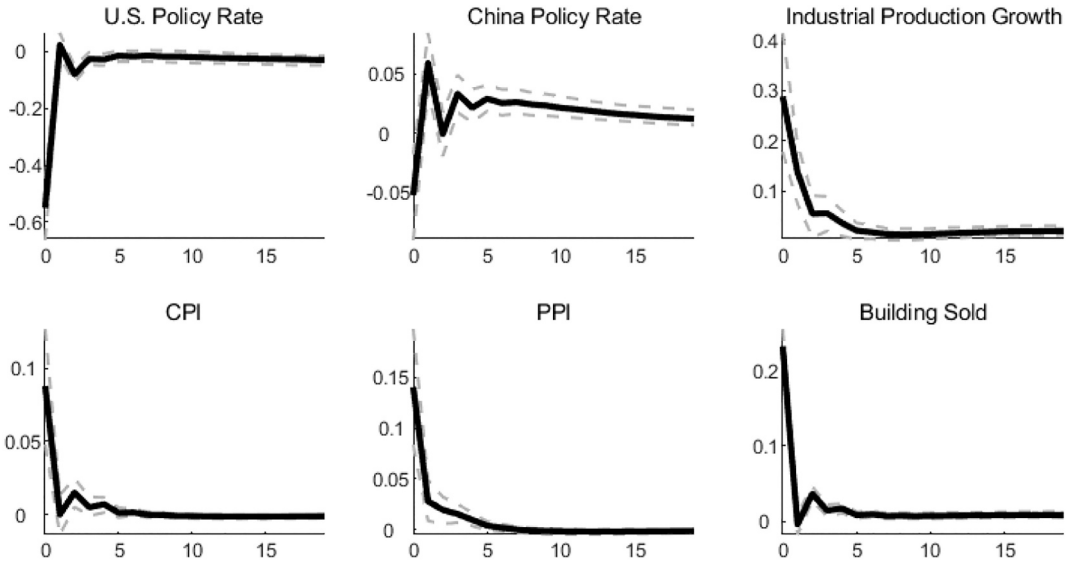


Fig. C.32. Impulse responses to the ASEAN factor (alternative order) (I).
Notes: Impulse responses to an ASEAN shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

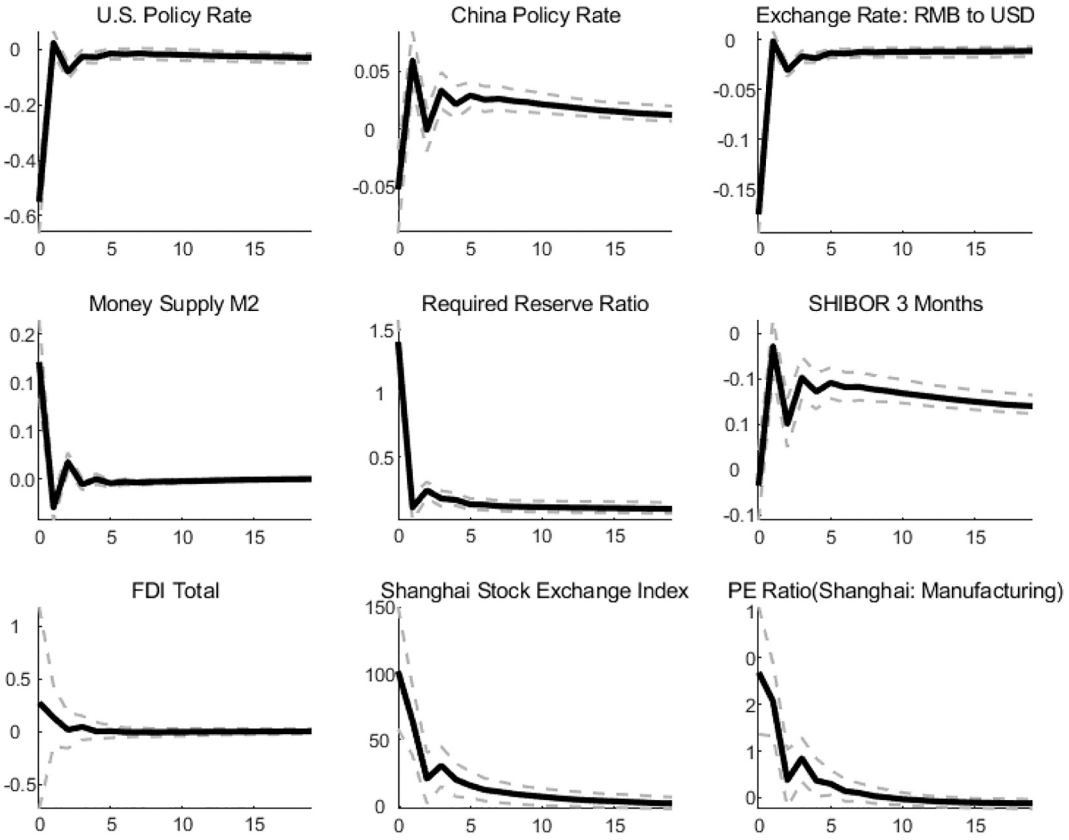


Fig. C.33. Impulse responses to the ASEAN factor (alternative order) (II).
Notes: Impulse responses to an ASEAN shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

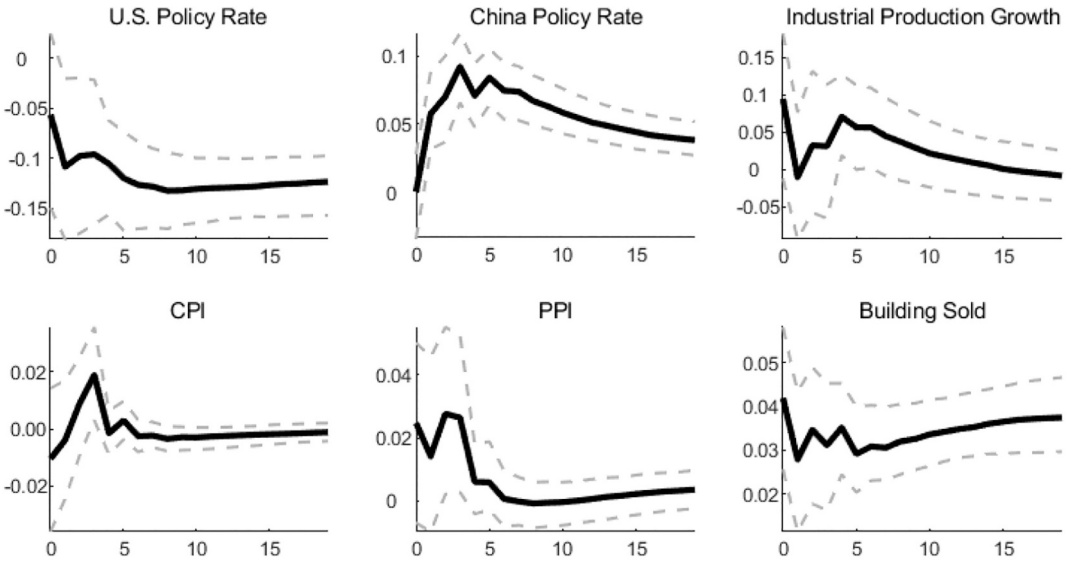


Fig. C.34. Impulse responses to the M&H-Tech factor (alternative order) (I).
Notes: Impulse responses to an M&H-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

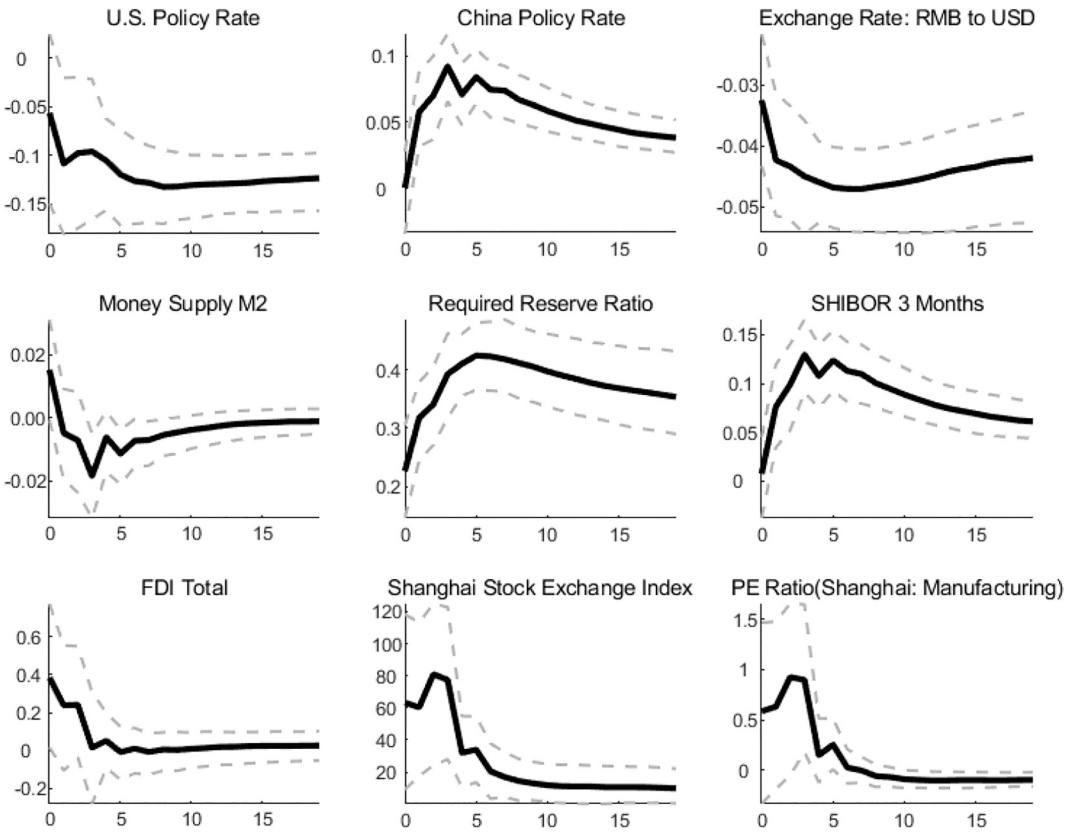


Fig. C.35. Impulse Responses to the M&H-Tech Factor (Alternative Order) (II).
Notes: Impulse responses to an M&H-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

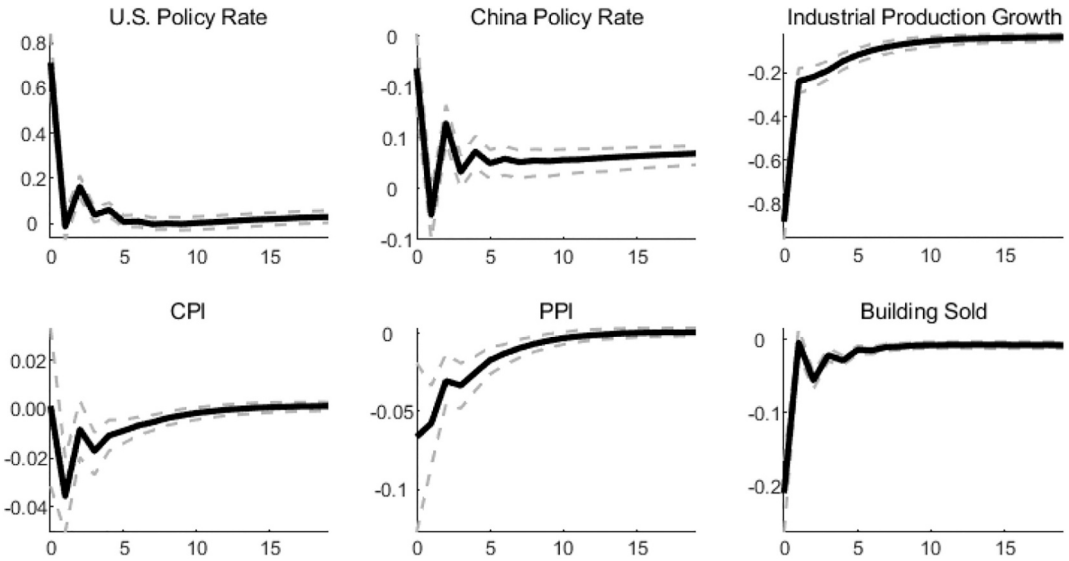


Fig. C.36. Impulse responses to the low-tech factor (alternative order) (I).
Notes: Impulse responses to a low-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

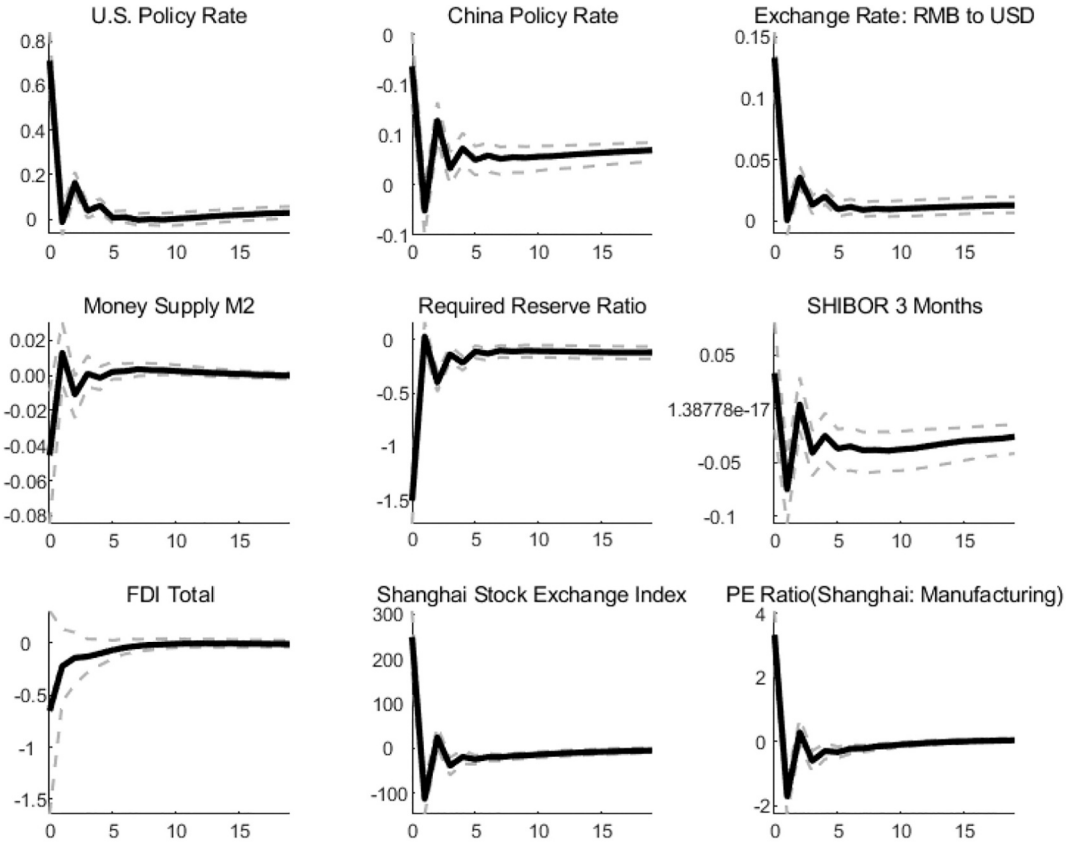


Fig. C.37. Impulse responses to the low-tech factor (alternative order) (II).
Notes: Impulse responses to a low-tech shock from 1 to 20 months, estimated using data from January 2001 to June 2023. The solid lines are the bootstrap medians, and the dashed lines are 84% bootstrap confidence intervals.

Data availability

Data will be made available on request.

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