What Happens in China Does Not Stay in China[*]

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Abstract

China's economy is the second largest in the world and account for more than 30% of global growth. Yet China's role as a driver of global economic and financial fluctuations is mostly uncharted. This paper quantifies China's role by addressing two key issues. First, we construct a measure of China's credit impulse to isolate Chinese policy induced demand shocks as Chinese authorities have a significant degree of control over the supply of credit to the economy. Second, we estimate a measure of alternative GDP growth that better captures the volatility of underlying Chinese economic activity as official GDP in recent years is seemingly overly smooth. The results from our structural VAR show that since the Great Financial Crisis, China plays a quantitatively important role in driving the global business and financial cycle. We find that a 1% of GDP stimulus in China's credit policies induces a 0.7% increase in its own GDP, a 1.2% increase in annual world industrial production reflecting a boost from higher Chinese demand. We also find that global credit outside of China increases by 0.4% driven by a rise in global risk appetite.

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1 Introduction

China's economy is the second largest in the world and accounts for more than a third of global growth. Its banking system, with $41 trillion in assets, is the largest in the world and is about double the size of that in the United States. As such, it is becoming critical to understand China's role as a source of shocks to both the global business cycle and to the global financial cycle–the global common movement of risky asset prices, capital flows, and leverage across borders–which, to date, is largely focused on United States (Rey, 2013; Miranda-Agrippino and Rey, 2020).

However, researchers aiming to understand China's role in the global economy are confronted with two significant hurdles. The first is the the difficulty of identifying Chinese demand shocks. As a major exporter, China is a recipient of shocks from, as well as a source of shocks to, the rest of the world. Moreover, the extensive yet nebulous role of the state in China's economy and financial markets, together with the use of non-standard policy instruments, greatly complicates the identification of policy changes that can be used to isolate Chinese demand shocks.

The second hurdle to an analysis of China's role in the global economy is Chinese data. To estimate the effect of China-induced policy shocks on the global business and financial cycle, one needs to first isolate the effect on the Chinese economy. However, Chinese GDP in particular has long been thought to be mismeasured (Rawski, 2001) and implausibly smooth (Nakamura et al., 2016)—a problem that has become acute in recent years (Clark et al., 2018; Fernald et al., 2021). Indeed, as we show in this paper, Chinese GDP growth in the past decade is smoother than that of any country in recent history (including China's own). Our paper seeks to address these problems and provide estimates of China's role in the global business and financial cycle.

We proceed in three steps. First, to isolate the effect of China-induced policy shocks on the global economy, we take advantage of the fact that the Chinese authorities exert a significant degree of control over the supply of credit to the economy. To that end, we construct a measure of the Chinese credit impulse, which is an aggregate of different types of credit influenced by the Chinese authorities, including bank loans, shadow credit, and local government bonds.

Second, to isolate the effects of Chinese demand shocks on the Chinese economy, we estimate an alternative measure of China's real GDP using a large set of indicators of economic activity that are believed to be less subject to smoothing by the government, including property market data, auto sales, reported exports to China from other countries, satellite nighttime lights data, and pollution data (Clark et al., 2018; Chen et al., 2019; Morris and Zhang, 2019; Groen and

Nattinger, 2020; Fernald et al., 2021). To construct an alternative GDP measure from these series, we employ a dynamic factor model (DFM), which is able to flexibly handle series of different lengths and frequencies—a particularly valuable property in the Chinese context—and has become an increasingly important tool for nowcasting a wide set of macroeconomic variables.

Lastly, we quantify the effects of shocks to China's credit impulse on global business and financial activity. We estimate a Bayesian vector autoregression (VAR) model that accounts for economic and financial developments to identify changes in the credit impulse due to government credit policies. We then estimate the effects of those policy-induced credit shocks on Chinese growth and its transmission to the rest of the world. This approach is preferred to directly estimating the impact of Chinese GDP on global activity, as movements in Chinese GDP could be endogenous to the global cycle.

We find that China's credit policies since the Great Financial Crisis (GFC) have had sizable effects on both global economic activity and global credit conditions. We estimate that a policy-induced 1 percentage point of GDP increase in China's credit impulse boosts its own economy 0.7 percent, proxied by an alternative measure of China's real GDP. After one to two years, the credit shock is estimated to induce a 1.3 percent rise in annual world industrial production excluding China and a 1.9 percent decrease in commodity prices, and raises world trade excluding China boosted by stronger Chinese demand.

Additionally, we find that China's credit policies have a significant effect on the global financial cycle—the co-movement of risky asset prices, capital flows, and leverage across borders(Miranda-Agrippino and Rey, 2020). Even though China's financial system is relatively closed to global investors, its influence reverberates through the global financial system by affecting Chinese economic developments and also global economic sentiment. Policy-induced expansionary credit shocks are estimated to reduce aggregate risk aversion, associated with a lower implied volatility of the SP 500 index, which increases global asset prices and credit.

Finally, we find that including our alternative measure for Chinese GDP is important in capturing the effect of China's credit policies on its own economy and studying the transmission of China's economy to the rest of the world. The VAR results show that an unexpected increase in the credit impulse generates a positive impact on Chinese GDP first and thus leads the subsequent movements in the global variables. In contrast, when we estimate our VAR with China's official GDP instead of our alternative measure, policy induced shocks to China's credit impulse do not significantly affect domestic output. We interpret this result as evidence of China's official GDP being seemingly overly smooth and, thereby, not capturing the cyclical movements. Therefore, this result underscores that our alternative measure of GDP is a useful proxy for activity. In addition, we find that identifying Chinese demand shocks using the credit impulse is another important factor to consider when studying China's contribution to the global cycle. Indeed, we find that a methodology where we use a shock to China's real GDP to study the spillovers to the rest of the world underestimates China's contribution to the global cycle. Specifically, we find limited effects on global industrial production but almost no significant impact on the global financial cycle.

Our paper contributes to the literature in several important ways. We contribute to an emerging literature that studies the global spillovers from China's economy Ahmed et al. (2019); Dizioli et al. (2016); Furceri et al. (2017); Gauvin and Rebillard (2018). To the best of our knowledge, this is the first paper that quantifies the role of Chinese demand shocks, measured by a more comprehensive Chinese credit measure, to the global business and financial cycle using an alternative growth measure for China. Relative to previous studies that quantify China's role in the global cycle, we find that China's importance might have been underestimated. Indeed, studies by Dizioli et al. (2016) and Furceri et al. (2017) find that the spillovers from China's economy to the global economy are relatively limited and are mostly confined to China's closest trading partners and commodity exporters. Likewise, Gauvin and Rebillard (2018) find that a structural slowdown in China would especially affect emerging market economies. In contrast, we find that China's economy has significant spillovers to global industrial production more generally. As such, we contribute to a large literature that studies the role of trade on global business cycle co-movovements (Baxter and Kouparitsas, 2005; Kose and Yi, 2001; Calderon et al., 2007; Liao and Santacreu, 2015). Specifically, Johnson (2014); Duval et al. (2015); de Soyres and Gaillard (2019, 2020) highlight the importance of trade in intermediate inputs as part of global value chains and its contribution to global GDP co-movements. de Soyres and Gaillard (2019) find that GDP co-movement is significantly associated with trade in intermediate inputs. Our results contribute to this literature in that we find that China's credit policies are estimated to be an important driver of global business activity though higher Chinese demand and subsequently higher global trade outside of China.

We also contribute to a large literature that studies the driving forces behind global financial cycles. Many studies have focused on the role of the United States, including Bruno and Shin (2015b,a); Miranda-Agrippino and Rey (2020), which establishes the importance of U.S. monetary policy as one of the main drivers of the global financial cycle. Similarly, recent work by Monnet and Puy (2019) studies global cycles for a wide set of emerging and advanced countries since 1950 and finds that business and financial cycles are generally driven by shocks that originate in the United States. We view our paper as shedding more light on the importance of another major economy, that is China, as its role still remains relatively unexplored. Our results indicate that China's credit policies since the GFC have been an important driver of the global financial cycle. We show that expansionary shocks to China's credit lead to a decline in aggregate risk aversion, associated with a higher implied volatility of the SP 500 index, which depresses global asset prices and credit. As such, our paper is most closely related to Miranda-Agrippino et al. (2020), which studies the global footprint of China's monetary policies using a monetary policy index based on Jia and Xu (2019)'s estimated natural interest rate to proxy the policy stance of the People's Bank of China. However, given that monetary policy and fiscal policy in China are intertwined and Chinese authorities view total domestic credit in the economy as an important policy objective, we construct a more comprehensive measure to identify Chinese demand shocks. Moreover, in contrast to Miranda-Agrippino et al. (2020), we find that China not only contributes significantly to the global business cycle, we find notable spillovers to global financial conditions. As such, to the best of our knowledge, this is the first paper that quantitatively shows China's important role as a driving force of the global financial cycle.

The remainder of the paper is organized as follows. Section 2 highlights several data issues that arise in analyzing the relationship between Chinese and global growth. Section 3 describes the estimation of the alternative growth series for China and the data series we use. Section 4 describes the quantitative analysis. Sections 5 presents the results. In section 6, we perform robustness analysis. Section 7 concludes.

2 Chinese Data Concerns

In this section, we highlight several key data issues in quantifying China's role in driving the global business and financial cycle.

2.1 China's credit impulse

Identifying policy shocks in the Chinese context presents a number of challenges. First, China's unique institutional setup blurs the line between fiscal, monetary, and regulatory policies, all of which are coordinated by the State Council, China's highest executive body. Second, China's policy framework has evolved continuously as its economy has developed; as such, policy instruments have also changed, making it difficult to compare policy shocks over time. Third, at any given time, Chinese authorities use a multiplicity of policy instruments to achieve their objectives, including many instruments for which we have poor visibility. Monetary policy, for example, is not centered around a key policy interest rate, but rather is executed by means of numerous instruments, including differentiated bank reserve requirements, administratively set interest rates for bank loan and deposit rates, short-term liquidity operations and rates on central bank lending facilities, open market operations to influence short-term market interest rates, and murkier instruments such as "window guidance" to banks on the amount of lending they may do. Similarly, fiscal policy since the Global Financial Crisis (GFC) has relied heavily on the use of off-budget quasi-government entities. Thus, it is difficult to assess the stance of policy based on any one policy instrument. Fourth, policy communications are generally constrained due to the presence of many stakeholders in Chinese policy decisions (Schipke et al, 2018), making it difficult to construct "news-based" measures that have proved a particularly promising approach to identifying policy shocks in other contexts (e.g., Gertler and Karadi, 2005; Jarocinski and Karadi, 2019?).

Rather than focusing on shocks to specific policy instruments, the approach we take in this paper is to focus on a key intermediate policy target—credit creation. Our approach takes advantage of the fact that a primary tool of Chinese stabilization policy—encompassing monetary, fiscal, and regulatory policies—is directing the flow and controlling the amount of credit in the economy. This reliance on credit dates back to the mid-1980s, in the early years of China's "reform and opening up," when the authorities switched from providing financing to state-owned enterprises (SOEs)—which at that time comprised most of the economy—via direct fiscal appropriations to providing indirect financing via bank loans (Chen and Zha, 2018). Credit supply was thus adjusted by tightening and relaxing loan quotas on state banks. In the early years, monetary policy played a largely passive role, as credit supply was largely determined by SOEs' financing needs in the context of soft budget constraints. Over time, as the inflationary consequences of this policy became apparent, monetary policy played a more active role by controlling the aggregate amount of credit in the economy—an aim of monetary policy that continues to this day (Chen and Zha, 2018).

Our preferred measure of the policy stance is the credit impulse, which measures the change in new credit in relation to GDP. The credit impulse has been shown in other contexts to be a useful measure of the impact of credit conditions on economic activity and is a closely watched metric of the policy stance among China watchers. To construct a comprehensive measure of the Chinese credit impulse, we aggregate different types of credit directly influenced by the Chinese authorities including bank loans, shadow credit, and local government bonds.

Although the People's Bank of China (PBOC) releases a monthly data series for domestic credit referred to as Total Social Financing (TSF), this is not a comprehensive set of all credit measures used by Chinese officials. In particular, in recent years, the Chinese authorities have relied heavily on local government bond issuance to invest in infrastructure and other projects. The TSF measure only includes a subset of those local government bonds, that is, *special* local government bonds.[1] Therefore, we first augment the TSF measure from the PBOC to include local government bonds. In addition, the TSF measure only dates back to 2002. We augment this TSF series by using data on renminbi denominated loans to track domestic credit in China back to 1990.[2] All told, we define aggregate credit as the PBOC's Total Social Financing less equity financing, plus local government bonds corrected for double counting of local government special bonds. This credit measure aggregates different types of credit including bank loans, shadow credit, and local government bonds.

The credit impulse is defined by the change in the flow of new credit in the past 12 months relative to those the year prior as a percent of nominal GDP. More formally, the credit impulse is measured at the monthly frequency and is denoted by

$$CI_m = \frac{\sum_{n=0}^{11} D_{m-n} - \sum_{n=12}^{23} D_{m-n}}{\sum_{n=12}^{23} Y_{m-n}}, \tag{1}$$

where m denotes the month, D_m is the level of additional monthly credit in the Chinese economy in month m, and Y_m is nominal official Chinese GDP. Note that Chinese GDP is only released at the quarterly frequency. Therefore, to impute monthly GDP, we divide total quarterly GDP evenly over the three corresponding months.

Figure 1 shows China's credit impulse together with its share in the global economy. It highlights that the Chinese authorities have actively used credit stimulus to stimulate and cool the economy since a long period. However, with China's rising share in the global economy, over the past several years, the quantitative importance of China's credit policies has risen notably.

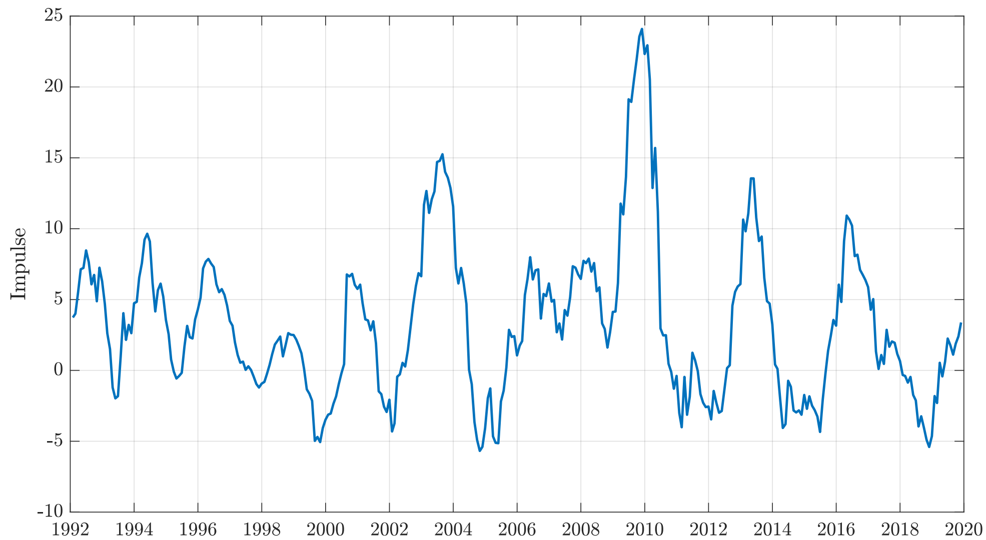
Finally, one important thing to note is that accounting for the usage of local government bonds in China is very important to correctly measure China's credit impulse. To underscore this point,

[1] In 2019, the PBOC changed its definition of Total Social Financing to include special local government bonds.

[2] In the 1990s renminbi denominated loans accounted for the bulk of domestic credit in China. The usage of local government bond issuance became a quantitatively important source of credit after the GFC. Similarly, the importance of shadow banking became quantitatively important after the GFC.

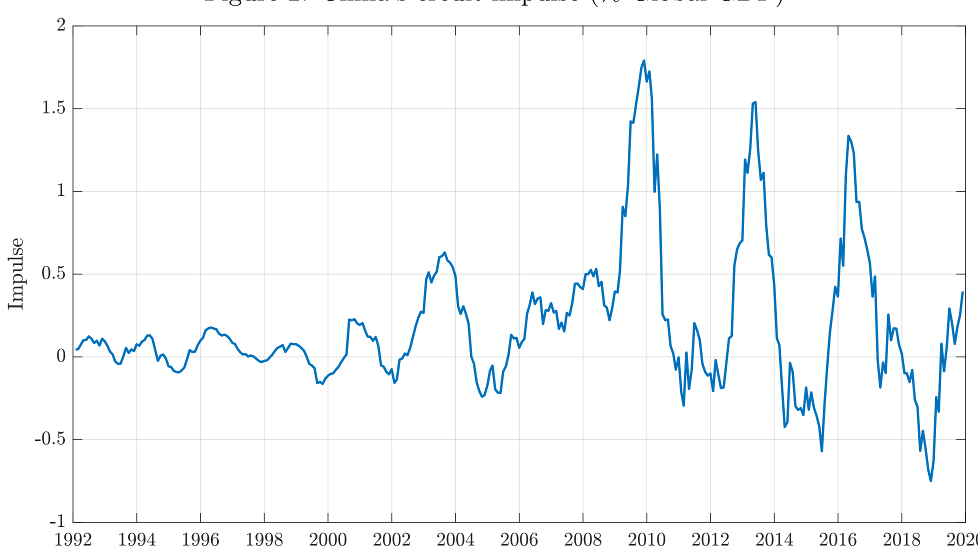
figure A.4 plots the credit impulse if we had not augmented the Chinese TSF series with the local government bonds. As figure A.4 highlights, Chinese authorities responded with massive stimulus after the 2014-2015 'China scare episode' but largely in part driven by local government bond issuance. According the TSF data, the stimulus period is identified incorrectly as taking hold only at the end of 2016.

Figure 1: China's credit impulse (% China's GDP)



Note: The impulse is calculated as the 12-month percent change in the 12-month rolling sum of the flow of new credit as a percent of 12-month lagged nominal GDP. Monthly GDP is computed as one third of quarterly nominal GDP for the corresponding quarter.

Figure 2: China's credit impulse (% Global GDP)



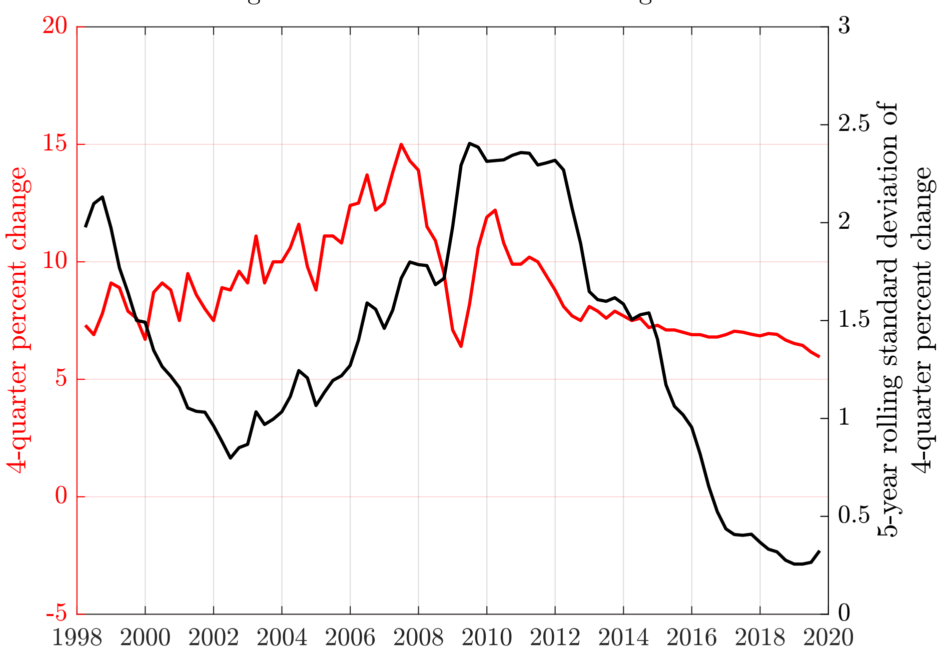
Note: The impulse is calculated as the 12-month percent change in the 12-month rolling sum of the flow of new credit as a percent of 12-month lagged global nominal GDP. Monthly nominal GDP is computed as one twelfth of annual nominal GDP.

2.2 Chinese real GDP

The second issue is the quality of China's GDP data. While this has been a longstanding concern, one key issue that has become especially acute over the past decade is that Chinese real GDP is seemingly overly smooth, as highlighted by Fernald et al. (2021), Clark et al. (2018), and Groen and Nattinger (2020). To underscore this point, figure 3 plots quarterly Chinese real GDP growth and its five-year moving standard deviation over the past decades. As figure 3 shows, the volatility of China's GDP growth has fallen markedly in recent years.

How does this volatility compare worldwide? Figure 4 plots the volatility of Chinese real GDP growth to all countries over time in history. It highlights that China's GDP volatility's is among the smoothest compared to all other countries. Additionally, in more recent years, that volatility is the lowest in China's own history and in all countries' history, suggesting that China's GDP might be overly smooth, especially in recent years.

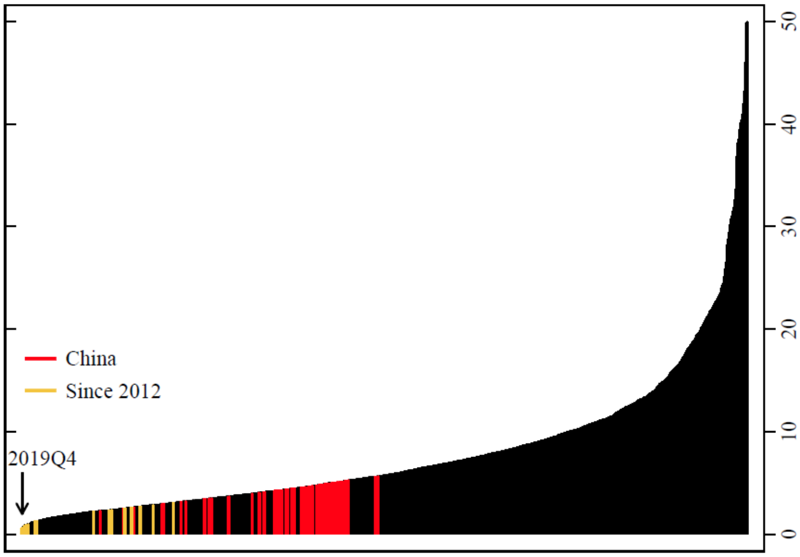
Figure 3: China's official real GDP growth



Note: Figure 3 plots China's official real GDP growth in 4-quarter changes its 5-year rolling standard deviation.

All told, using China's official GDP growth to study its role in the global cycle might mitigate or even mask the estimated transmission of a Chinese shock to the rest of the world. To address this concern regarding China's GDP, we estimate an alternative measure of China's real GDP using a dynamic factor model (DFM) as described in section 3.

Figure 4: China's GDP volatility compared to other countries



Note: Figure 4 plots the historical country rank of countries' 5-year rolling standard deviation of real GDP growth in 4-quarter changes across 101 countries for which at least 5 years of quarterly data is available. Values greater than 50 are omitted.

3 Estimation

3.1 Dynamic Factor Model

We employ a dynamic factor model (DFM, henceforth) to estimate the underlying path of China's economy. DFMs are a useful tool for monitoring macroeconomic conditions in real time (Giannone et al., 2008), being the ideal machinery candidate to summarize a large set of non-synchronous, disconnected data. The idea here is that Chinese observed variables, both monthly ($\mathbf{y_{m,t}}$) and quarterly ($\mathbf{y_{q,t}}$), are driven by a smaller number of latent unobserved factors ($\mathbf{f_t}$). Specific features of each series are captured by idiosyncratic errors ($\mathbf{e_{m,t}}$ and $\mathbf{e_{q,t}}$). Observable variables are linked to the factors by two set of observation equations, defined as

$$\begin{bmatrix} \mathbf{y_{m,t}} \\ \mathbf{y_{q,t}} \end{bmatrix} = \begin{bmatrix} \mathbf{\Lambda_m} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{\Lambda_q} & 2\mathbf{\Lambda_q} & 3\mathbf{\Lambda_q} & 2\mathbf{\Lambda_q} & \mathbf{\Lambda_q} \end{bmatrix} \begin{bmatrix} \mathbf{f_t} \\ \mathbf{f_{t-1}} \\ \mathbf{f_{t-2}} \\ \mathbf{f_{t-3}} \\ \mathbf{f_{t-4}} \end{bmatrix} + \begin{bmatrix} \mathbf{e_{m,t}} \\ \mathbf{e_{q,t}} \end{bmatrix}, \tag{2}$$

while factors are defined by the transition equations

$$\mathbf{f_t} = \mathbf{A_1 f_{t-1}} + ... + \mathbf{A_p f_{t-p}} + \mathbf{u_t}. \tag{3}$$

$\mathbf{y_{m,t}}$ and $\mathbf{y_{q,t}}$ are vectors of n_m monthly and n_q quarterly data, respectively, while $\mathbf{f_t}$ is a vector of r latent factors. Monthly and quarterly variables are standardized stationary, and the common factors have mean zero and unit variance.

The matrices $\mathbf{\Lambda_m}$ and $\mathbf{\Lambda_q}$ summarize the factor loadings of the monthly and quarterly variables, $\mathbf{e_{m,t}}$ and $\mathbf{e_{q,t}}$ are vectors of idiosyncratic components uncorrelated with $\mathbf{f_t}$ at all leads and lags. We link the monthly growth rates to its quarterly counterpart using the aggregation procedure proposed by Mariano and Murasawa (2003). The matrices $\mathbf{\Lambda_m}$ and $\mathbf{\Lambda_q}$ can be full, and so all monthly and quarterly variables load on all r factors. Another option is to restrict specific loadings of each matrix to zero. The advantage of such a procedure is to bring economic intuition to the estimated factor. One could choose, for example, to load variables only linked to a specific industry (like manufacturing), and then the factor would have an industry-specific interpretation.

The matrices A_1 to A_p bring a VAR-like structure to the latent factors. If only one factor is selected, then it follows an AR(p) process. If $r > 1$ factors are selected, the matrices A_1 to A_p can be unrestricted and these factors interact in a VAR(p) structure, or can be restricted to a diagonal and the factors will be estimated individually as AR(p) processes.

As a benchmark, we define here our measure of alternative Chinese growth as a DFM projection of the variables described in the next Section, with 2 factors, with $p = 1$ lag, and each factor estimated as an AR(1) process. We estimate alternative structures with less factors, restricted manufacturing and/or services factors, and VAR structures, and the results presented here are robust to these variations.

3.2 Data

In order to estimate the dynamic factor model (DFM) as described in the previous section, we need data series that reflect underlying economic activity in China. Before we describe which data series we use in our analysis, we first discuss several issues regarding data selection.

The first issue is that certain data series are highly correlated with official GDP growth. Therefore, these series are likely also smoothed. Particularly, we find that industrial production and retail sales are highly correlated with official GDP and if we estimate a DFM with those factors, our alternative

GDP series resembles the official GDP growth series very closely. In addition, Chen et al. (2019) also find issues with industrial production data. Therefore, in a robustness analysis, we will exclude those series.

The second issue is that China's economy has undergone a structural structural shift from an investment-led and export dependent country to a more consumption based country. Consequently, to reflect underlying growth, our estimation needs data series that reflect those parts of the economy. We do so by including series such as semiconductor production, mobile phone production, auto sales, and property market starts. As highlighted earlier, a number of these series have relatively short time spans compared to more manufacturing based series. Therefore, the benefit of the DFM estimation is that this method allows for series with different time horizons.

Therefore, we will use a combination of: (1) traditional Chinese series, (2) Chinese series believed to be 'less smoothed' used in other papers, (3) Chinese series, believed to be 'less smoothed' considered in this paper to better capture consumption in China, and (4) series from non-Chinese agencies. The series we consider include:

1. **Traditional Chinese series**: industrial production, retail sales, total fixed asset investment, official manufacturing PMI[3];

2. **Chinese series believed to be less subject to smoothing used in other papers**: exports, railway freight, electricity consumption, electricity production, cement production, consumer expectation index, industrial profits, Caixin manufacturing PMI, floor space sold, floor space started, iron ore imports, steel production;

3. **Chinese series, believed to be less subject to smoothing considered in this paper**: auto sales, fixed asset investment for the manufacturing sector, fixed asset investment for the services sector, excavator sales, household items production, copper import volume, microcomputer production, semiconductor production;

4. **Series from non-Chinese agencies**: Chinese imports (computed by foreign reported exports), Alibaba sales, Lenovo sales, Tencent sales, nitrogen dioxide (NO2), satellite nightlights.

[3]Even though we believe some of these traditional Chinese series exhibit similar smoothness properties as official real GDP, we include them in the set of possible variables to let the DFM determine which series to place a higher weight on. As such, we take a more agnostic approach as to which series to include or not.

3.3 Alternative growth

Our preferred model uses a wide set of all previously described series.[4] In section 6 we consider additional specifications. To estimate our alternative growth measure we do the following steps:[5]

1. We take series in 12-month growth rates;[6]

2. Estimate the DFM from January 2000 through December 2019 and extract one global factor;

3. Convert the global factor movements into GDP movements:

   - First, regress the global factor on (de-trended) official real GDP growth in 4-quarter percent changes.[7]

   - Second, use this elasticity to map global factor movements into GDP growth in 4-quarter percent changes.

   - Finally, add the trend of official real GDP growth back in. The underlying assumption is that, on average, trend growth from China's official real GDP correctly represents that of the Chinese economy.

Figure 5 plots our estimated alternative Chinese growth series and compare to the officially reported growth. There are several takeaways. The first is that our estimated alternative growth captures the overall path of official growth relatively well. Specifically, the model matches well the GFC movements and the subsequent downturn following the GFC.

The second takeaway is that our estimated alternative growth is more volatile than official growth in recent years. More specifically, we find that the 2015 slowdown was more pronounced than officially reported. Specifically, we find that Chinese growth in 2015 slowed to 6%, which is a full percentage point lower than officially reported. In addition, the post-2015 recovery was stronger than officially reported. Our alternative growth estimate shows that Chinese growth rose to near 7.5 percent, whereas official GDP growth shows a growth rate of about 6.8 percent. Finally, the slowdown following the Chinese authorities' deleveraging campaign has caused growth to slow more rapidly than officially reported and dipped below official growth in the second half of 2018.

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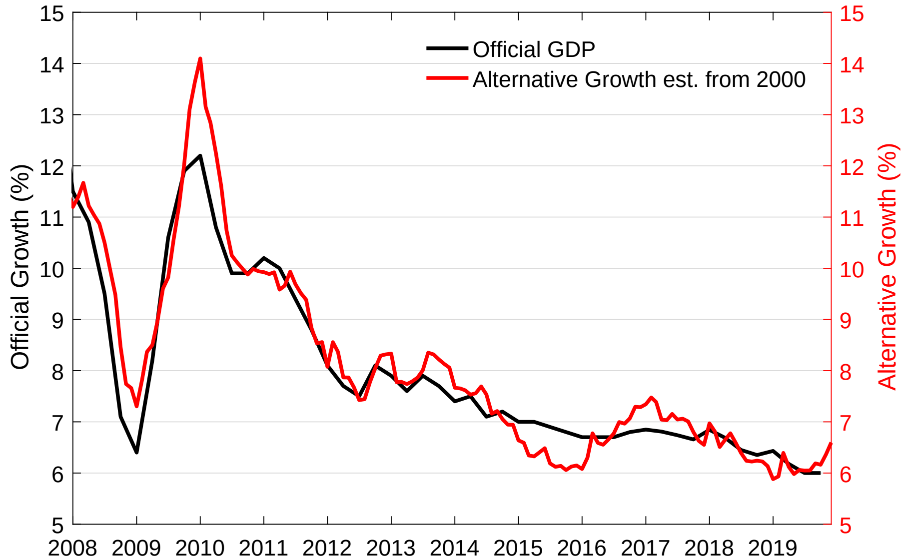
[4] See table A.1 in the appendix for the exact model specifications.

[5] We perform numerous robustness tests that relaxes some of the underlying assumptions in these steps.

[6] The exceptions include PMI series and consumer confidence index, which are used in levels. We choose to estimate the DFM in 12-month changes to mitigate measurement issues regarding the underlying Chinese data. Indeed, the majority of China's data series are reported in 12-month or year-to-date 12-month percent changes as opposed to typical level series.

[7] Trend and cycle of GDP extracted using the Hodrick–Prescott filter.

Figure 5: Alternative versus Official Growth



Note: Figure 5 plot China's official real GDP growth in 4-quarter changes and our preferred alternative Chinese GDP growth in 12-month changes.

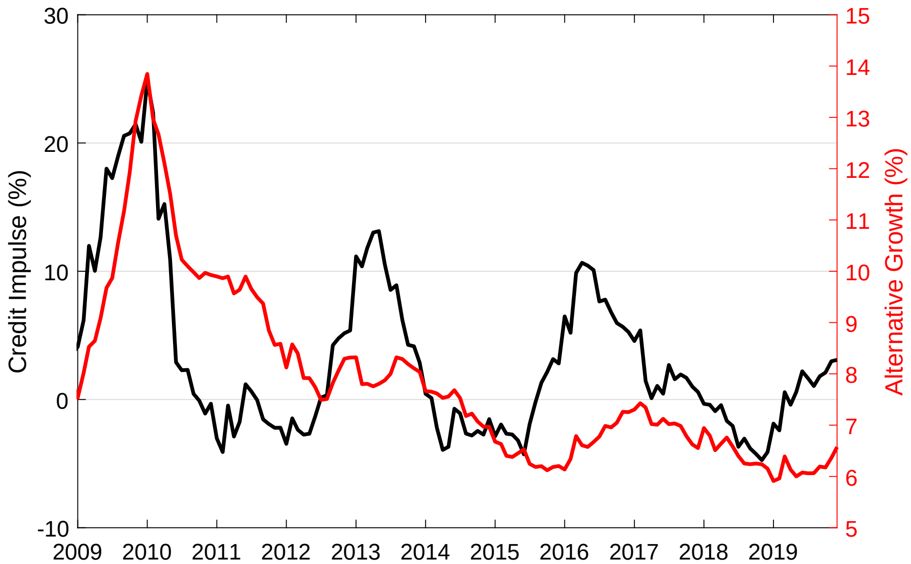
If we compare our alternative measure to the credit impulse, the impact of credit policies is more apparent as highlighted in figure 6. This is particularly striking because we have not included any credit measures in our DFM estimation such as household loans or banks loans. Even so, the credit impulse appears to lead our alternative growth indicator. This result motivates our analysis of how much China drives the global cycle as described in the next section.

3.4 Monthly growth estimates and alternative GDP level

In the previous section, we constructed our preferred alternative measure for monthly Chinese growth in 12-month changes. But, in order to estimate the VAR, we need to convert these growth rates into GDP levels. However, there is no GDP level series that is uniquely identified from these 12-month growth rates. Moreover, its estimation is complex due to the non-linearity implied by the 12-month compounding of the unobserved monthly series. In this subsection, we propose a method to extract underlying month-to-month growth rates, and thereafter construct an alternative measure for the level of Chinese GDP

Our method is based on the Mariano and Murasawa (2003) quarterly aggregation, adapted to the growth rate of one quarter over the same quarter of the previous year. The procedure approximates the geometric mean of the monthly growth rates to an arithmetic mean, in order to make the estimation linear. Following the same notation from Mariano and Murasawa (2003), let Y_t represent

Figure 6: Alternative Growth and the Credit Impulse



Note: Figure 6 plot China's credit impulse and our preferred alternative Chinese GDP growth in 12-month changes.

a quarterly indicator observed every third period, such as the (observed) quarterly GDP level, and Y_t^* a latent monthly indicator, such as the monthly (unobserved) GDP level. Y_t and Y_t^* relates as

$$\log Y_t = \frac{1}{3}(\log Y_t^* + \log Y_{t-1}^* + \log Y_{t-2}^*), \tag{4}$$

where Y_t is the geometric mean of Y_t^*, Y_1^*, and Y_{t-2}^*. Taking the 12-period differences we can reconstruct the equivalent of a quarter over the same quarter of the previous year, as in

$$\log Y_t - \log Y_{t-12} = \frac{1}{3}(\log Y_t^* - \log Y_{t-12}^*) + \frac{1}{3}(\log Y_{t-1}^* - Y_{t-13}^*) + \frac{1}{3}(\log Y_{t-2}^* - Y_{t-14}^*). \tag{5}$$

Adding and subtracting lagged values of $\log Y_t^*$ leads to

$$\begin{aligned}
&\log Y_t - \log Y_{t-12} = ...\\
&\frac{1}{3}(\log Y_t^* - \log Y_{t-1}^* + \log Y_{t-1}^* - \log Y_{t-2}^* + \log Y_{t-2}^* - ... + \log Y_{t-11}^* - \log Y_{t-12}^*) + ...\\
&... + \frac{1}{3}(\log Y_{t-1}^* - \log Y_{t-2}^* + \log Y_{t-2}^* - \log Y_{t-3}^* + \log Y_{t-3}^* - ... + \log Y_{t-12}^* - \log Y_{t-13}^*) + ...\\
&... + \frac{1}{3}(\log Y_{t-2}^* - \log Y_{t-3}^* + \log Y_{t-3}^* - \log Y_{t-4}^* + \log Y_{t-4}^* - ... + \log Y_{t-13}^* - \log Y_{t-14}^*).
\end{aligned} \tag{6}$$

Defining $y_t = \log Y_t - \log Y_{t-12} = \Delta_{12} \log Y_t$ as the growth rate of the quarter over the over the same quarter of the previous year, observed every three months, and $y_t^* = \log Y_t^* - \log Y_{t-1}^* = \Delta \log Y_t^*$ the monthly growth rate, never observed, the previous equation can be written as

$$y_t = \frac{1}{3}(y_t^* + ... + y_{t-11}^*) + \frac{1}{3}(y_{t-1}^* + ... + y_{t-12}^*) + \frac{1}{3}(y_{t-2}^* + ... + y_{t-13}^*), \tag{7}$$

or simply

$$y_{1,t} = \frac{1}{3}y_t^* + \frac{2}{3}y_{t-1}^* + y_{t-2}^* + ... + y_{t-11}^* + \frac{2}{3}y_{t-12}^* + \frac{1}{3}y_{t-13}^*. \tag{8}$$

Equation 8 represents a linear approximation that connects the observed quarter over the over the same quarter of the previous year growth rate to the unobserved monthly growth rate. This relation can be conveniently estimated as a state-space model described by

$$\begin{bmatrix} y_t \\ y_t^* \\ y_{t-1}^* \\ y_{t-2}^* \\ ... \\ y_{t-11}^* \\ y_{t-12}^* \end{bmatrix} = \begin{bmatrix} 0 \\ c_0 \\ 0 \\ 0 \\ ... \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1/3 & 2/3 & 1 & ... & 1 & 2/3 & 1/3 \\ 0 & c_1 & 0 & ... & 0 & 0 & 0 \\ 0 & 1 & 0 & ... & 0 & 0 & 0 \\ 0 & 0 & 1 & ... & 0 & 0 & 0 \\ ... & ... & ... & ... & ... & ... & ... \\ 0 & 0 & 0 & ... & 0 & 1 & 0 \\ 0 & 0 & 0 & ... & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_t^* \\ y_{t-1}^* \\ y_{t-2}^* \\ y_{t-3}^* \\ ... \\ y_{t-12}^* \\ y_{t-13}^* \end{bmatrix} + \begin{bmatrix} 1/3 & 0 & 0 & ... & 0 & 0 & 0 \\ 1 & 0 & 0 & ... & 0 & 0 & 0 \\ 0 & 0 & 0 & ... & 0 & 0 & 0 \\ 0 & 0 & 0 & ... & 0 & 0 & 0 \\ ... & ... & ... & ... & ... & ... & ... \\ 0 & 0 & 0 & ... & 0 & 0 & 0 \\ 0 & 0 & 0 & ... & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_t \\ 0 \\ 0 \\ 0 \\ ... \\ 0 \\ 0 \end{bmatrix}, \tag{9}$$

where the monthly growth rate y_t^* follows an AR(1) with $u_t \sim N(0,1)$. Since the model is linear in the unobserved monthly growth rate, it is possible to apply the Kalman filter to evaluate the likelihood function and estimate the parameters through maximum likelihood.[8]

We construct our alternative GDP monthly growth rate by estimating the state-space model 9 taking as a signal y_t, our monthly year-over-year alternative growth rate described in Section 3.3 and exhibited in Figure 5.

The approximation of the geometric mean through an arithmetic mean leads to almost negligible errors if monthly changes are small (Camacho and Perez-Quiros, 2010). However, two issues arise with our implementation. First, an approximation of 12-month growth rates exacerbates the approximation error as it accumulates 12 monthly rates instead of only three in the case of

[8]See Stock and Watson (1991) and Mariano and Murasawa (2003) for details on the estimation procedure.

quarterly growth rates. Second, China's annual GDP growth ranges from six to 12 percent in recent years, which implies that monthly changes are not small. We deal with this issue by adjusting the estimated log-difference monthly GDP by a factor that best approximates its arithmetic mean to the geometric mean. In practice, we construct the monthly GDP level as

$$Y_t^* = Y_{t-1}^* x^{y_t^*/100}, \tag{10}$$

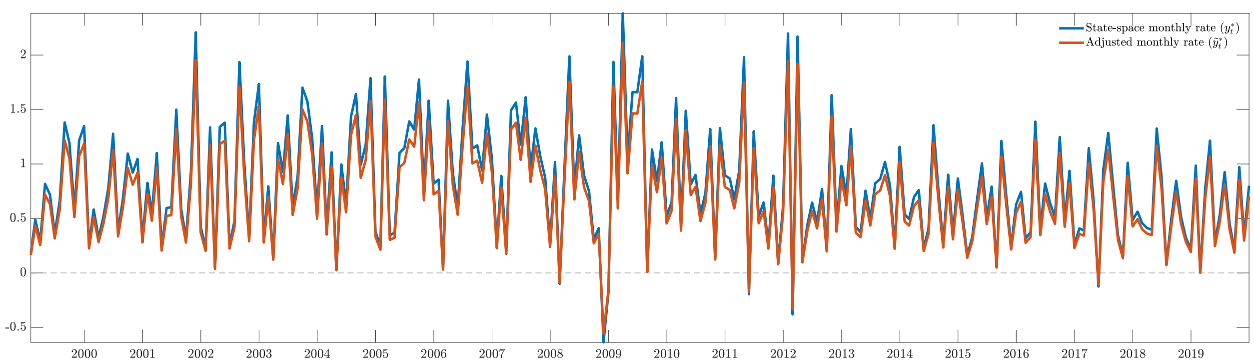
where x is the number that minimizes the error[9]

$$\min_x \frac{\sum_{t=1}^{T} \left(y_t - \left(\frac{(Y_t^* + Y_{t-1}^* + Y_{t-2}^*)}{(Y_{t-12}^* + Y_{t-13}^* + Y_{t-14}^*)} - 1 \right) * 100 \right)^2}{T}, \tag{11}$$

and the adjusted monthly growth rate $\tilde{y}_t^*$ as

$$\tilde{y}_t^* = \left(\frac{Y_t^*}{Y_{t-1}^*} - 1 \right) * 100. \tag{12}$$

Figure 7: Monthly GDP growth rate



Note: Figure 7 plots the monthly growth rates that are estimated in a state-space model taking signal from our alternative 12-month growth rate, denoted by y_t^*, estimated using a dynamic factor model, and the adjusted monthly growth rates, denoted by $\tilde{y}_t^*$, as computed by equation 12.

4 Quantitative Analysis

To quantify the economic effects of China's credit policies on the global cycle, we estimate a monthly Bayesian VAR in levels that includes variables capturing the overall state of global business activity, global financial conditions, and China's economic activity. We then evaluate the transmission effects

[9] We estimate x as 2.396, which is slightly smaller than the Euler's number.

of unexpected changes in Chinese credit. The reason why we opt for a shock to China's credit impulse is that the Chinese authorities exert a significant degree of direct control over the supply of credit to the economy. As such, this allows us to identify demand shocks that originate from China. Moreover, this approach is preferred to directly estimating the impact of Chinese GDP on global activity, as movements in Chinese GDP could be endogenous to the global cycle.

We estimate a monthly VAR with 12 lags and an intercept term:

$$\mathbf{y}_t = \mathbf{B}_1 \mathbf{y}_{t-1} + ... + \mathbf{B}_p \mathbf{y}_{t-p} + \epsilon_t. \tag{13}$$

Table 1 describes the variables we include in our different VAR specifications. We first estimate a narrow VAR with only four variables (model (1)) to study China's contribution to the global business cycle, as measured by the global economic conditions index constructed by Baumeister et al. (2021), and to the global financial cycle, constructed by Miranda-Agrippino and Rey (2020).

Then we estimate our benchmark VAR (model (2)) to quantify the spillovers of China's credit policies and study the channels of transmission. This benchmark VAR (model (2)) includes twelve endogenous variables: the VIX (VIX), which is an index of the implied volatility in S&P500 stock index option prices from the Chicago Board Options Exchange (CBOE), the S&P500 stock market index. a commodity price index, global exports excluding Chinese exports, global industrial production excluding China, the broad U.S. dollar, the 2-year U.S. Treasury yield, global credit flows excluding China, global inflows into banks, and global inflows into non-banks. With the exception of the 2-year U.S. Treasury yield and the credit impulse, all variables are level series at the monthly frequency.

The VAR models are estimated with 12 lags and an intercept term for three subsamples: from January 2000 to April 2019, from January 2009 to April 2019, and from January 2012 to April 2019.[10] We employ a Bayesian VAR in order to estimate the large number of coefficients and we take advantage of Minnesota priors (Litterman, 1986; Bańbura et al., 2010). Confidence bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution.

The variables in all estimated VARs are summarized in table 1. We identify a credit impulse shock through a recursive Cholesky decomposition in a block exogeneity structure, where the credit impulse is ordered first after all the indicators, including China's alternative GDP. This structure assumes that an exogenous credit impulse shock can affect the rest of the world and China only

[10] Note that end period constrained by the measure for the global financial cycle as constructed by Miranda-Agrippino and Rey (2020), which is updated through April 2019.

Table 1: VAR Variables

Variable name	Source	Model			
		(1)	(2)	(3)	(4)
China's credit impulse	Own calculation	x	x	x	
Alternative Chinese real GDP	Own calculation	x	x		
Global financial cycle indicator	Miranda-Agrippino and Rey (2020)	x			
Global economic conditions index	Baumeister et al. (2021)	x			
VIX	Haver		x	x	x
S&P500 index	Haver		x	x	x
Broad U.S. dollar	BIS*		x	x	x
2-year U.S. Treasury yield	FRB		x	x	x
Global credit flows ex. China	BIS*, Own calculation		x	x	x
Global inflows to banks	BIS*		x	x	x
Global inflows to non-banks	BIS*		x	x	x
Commodity price index	Haver		x	x	x
Global Trade ex. China	Haver, Own calculation		x	x	x
Global IP ex. China	Haver, Own calculation		x	x	x
Global GDP ex. China	Haver, Own calculation		x	x	x
Official Chinese real GDP	NBS*			x	x
Figures	2012-2019	8	9	11	12

Note: The top panel in table 1 lists the variables included in our different VAR model specifications. The NBS is the National Bureau of Statistics in China. * denotes monthly interpolation of the quarterly original variables using a piecewise cubic interpolation. The bottom panel in table 1 describes the corresponding figures of each model estimation and for different time spans.

with a one-month lag.

Formally, taking a vector of endogenous variables $\mathbf{y}_t$, the moving average representation (in levels) is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{14}$$

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{15}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{16}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the impact matrix that makes $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$ (variance-covariance matrix of innovations). We take $\mathbf{A}_0$ as the lower triangular Cholesky factor of the covariance matrix of reduced-form innovations.

5 Results

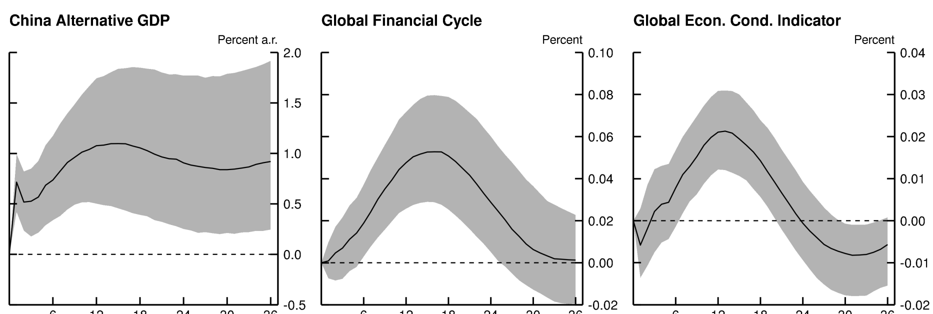
In this section, we first present the results of a narrow model to capture China's contribution to the global business and financial cycle as measured by aggregated factors. Then, we study the mechanisms of how China's credit policies spill over to the rest of the world. Finally, we highlight the importance of using China's credit impulse to identify policy induced Chinese demand shocks and the usage of our alternative GDP measure for China.

5.1 Narrow Model

First, we analyze the effects of a Chinese credit impulse shock on China's economy and its transmission to aggregate global business activity and global financial conditions. As highlighted in the previous section, we estimate a four-variable VAR (model (1) in table 1). We focus on the period after the Global Financial Crisis–from January 2012 to April 2019–when China's footprint in the global economy is largest. The reason why we first estimate this narrow model is to focus on business and financial cycle aggregates, thereby reducing the number of parameters estimated, especially given the relatively short time horizon.

Figure 8 presents the results and we also include the 16th and 84th percentiles of the impulse response results for the draws from the posterior distribution. We find that a one percentage point increase in China's credit impulse leads to a significant rise in Chinese GDP of about 0.7%. The positive effects are strongest around 16 months.

Figure 8: Economic responses to a 1% (of GDP) credit impulse shock (2012-2019)



Note: The lines in figure 8 are the estimated impulse responses to a 1 percent of Chinese GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 1 for the VAR specification.

In addition, figure 8 highlights that China's expansive credit policies positively and significantly affect the global economic conditions index as constructed by Baumeister et al. (2021). Interestingly, we find that the upturn in our alternative Chinese GDP measure leads the significant impact on the global economic conditions index, pointing to the transmission of higher Chinese demand to the rest of the world.

Next, we consider the effects of China's credit policies on global financial conditions. Figure 8 highlights that a positive shock to China's credit impulse notably eases global financial conditions. The impulse response functions show a positive and significant impact on the global financial cycle indicator constructed by Miranda-Agrippino and Rey (2020). The effects are strongest after 18 months and therefore, lag the positive effects on Chinese GDP, which again points to the transmission from China's economy to the rest of the world and not vice versa.

All told, the results from our narrow model show that China's credit policies since the GFC have a significant impact on the global business and financial cycle. Moreover, we find evidence that the transmission occurs from China's economy to the rest of world. Note, however, that these are aggregate measures. In the next section, we estimate a VAR with disaggregated data. This serves two purposes. The first is to *quantify* China's contribution to economic and financial activity. Second, it allows us to study in detail the mechanisms of how China's credit policies spill over to the rest of the world.

5.2 Benchmark Model

Our benchmark VAR includes 12 endogenous variables as described in table 1 (model (2)) and is estimated from January 2012 to April 2019. We present the impulse responses after an unexpected, one standard deviation increase in the 12-month Chinese credit impulse. We also include the 16th and 84th percentiles of the impulse response results for the draws from the posterior. Figure 9 presents the impulse responses. By construction, all variables do not react on impact.

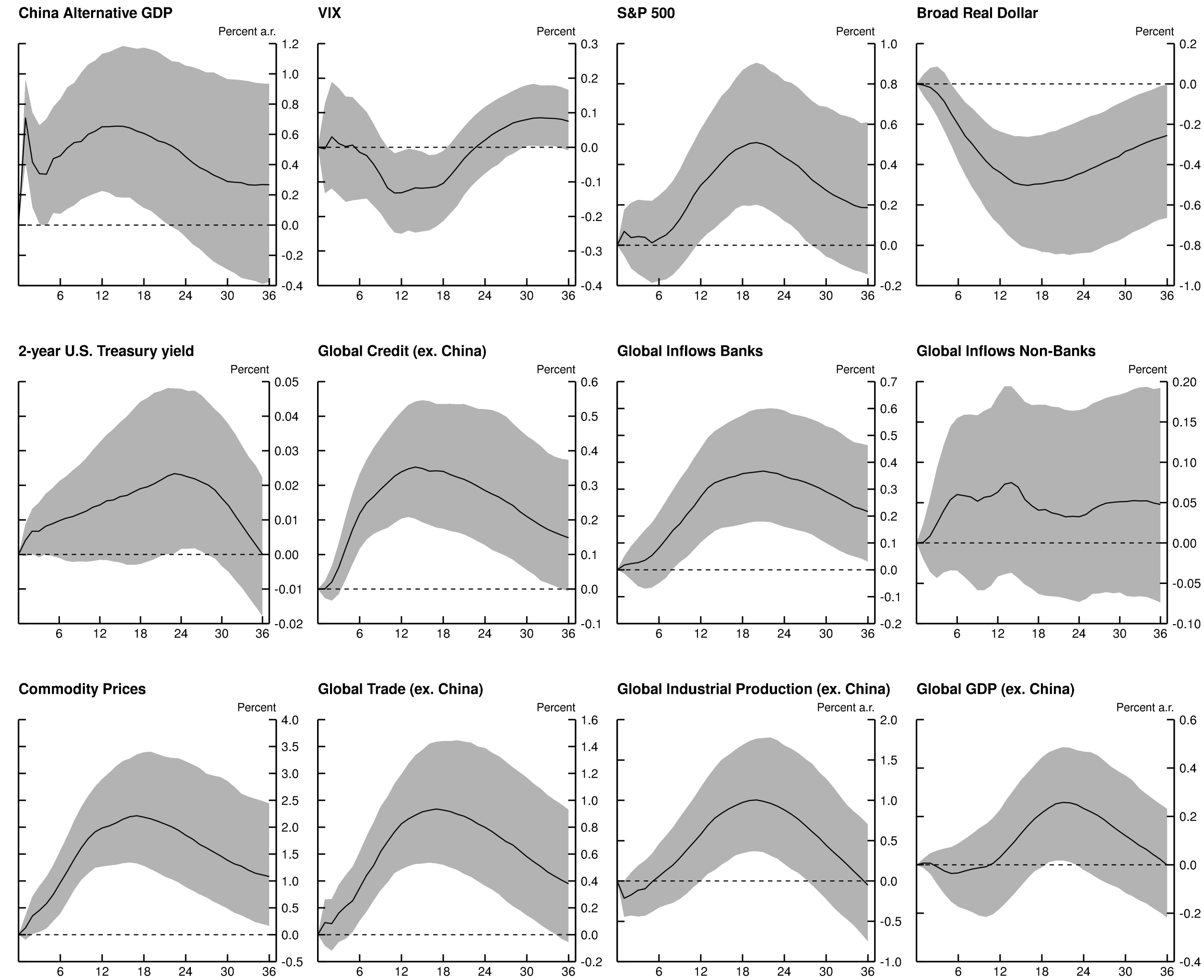
First, we consider the effects of China's expansive credit policies on on the Chinese economy using our alternative growth measure and global business activity. We find that a positive shock to China's credit impulse leads to a positive and significant increase in Chinese GDP in the medium run. The impulse response functions show that the strongest effects on China's GDP occur after 16 months with positive effects for just under 24 months. Specifically, we find that a positive shock to China's credit policies of one percentage point of Chinese GDP, leads to a 0.7% rise in China's alternative GDP measure. This result highlights that China's credit policies constitute an important driver of fluctuations in Chinese GDP.

Next, we consider the effects on real economic activity outside of China. We find that China's expansive credit policies lead to an increase in global trade excluding China. Figure 9 shows that global trade (excluding China) increases significantly in the medium run, but with a lag compared to China's economic activity. Specifically, we estimate that a positive shock to China's credit policies of one percentage point of Chinese GDP–about $149 billion–induces an increase in global trade outside of China of about 1%, which points to quantitative strong Chinese demand spillovers. Moreover, we find that stronger Chinese demand leads to an increase in commodity prices. We find that commodity increase 1.9% after a shock to China's credit of one percentage point of Chinese GDP, peaking around 16 months after the shock. This result is complementary to Fernández et al. (2020), in that we formally identify China as an important driver of commodity price movements.[11] In addition to an increase in commodity prices, 9 shows that global industrial production (excluding China) also increases significantly in the medium run, and, again, with a lag compared to China's economic activity. Specifically, we estimate that a positive shock to China's credit policies of one percentage point of Chinese GDP induces an increase in global production of about 1.2%, which amounts to around $20 billion. Moreover, our estimated measure for Chinese growth peaks after around 16 months, global industrial production outside of China peaks only after around 20 months. This lagged response indicates that the positive effects of China's credit impulse are transmitted to the rest of the world, driven by a boost to global manufacturing. The delayed effect also indicates that the initial transmission direction is from the Chinese economy–through higher Chinese demand–to the rest of the world, and not the reverse where increased global demand boosts Chinese activity.

After studying the effects of China's expansive credit policies on business activity, we now consider the effects on global financial conditions. Figure 9 highlights that China's expansive credit policies lead to an increase in global credit outside of China. Moreover, we find a positive and significant effects on global inflows into banks. The effects are strongest after about 18 months and therefore, lag the positive effects on Chinese GDP, which again points to the transmission from China's economy to the rest of the world and not vice versa. This resulting might be somewhat surprising given that China's financial system is still relatively closed to global investors. But what the impulse response functions in figure 9 also highlight is that a positive shock to China's credit impulse leads to an increase in global investor sentiment. Indeed, we find a significant decline the

[11] Fernández et al. (2020) show that world shocks that affect commodity prices and the world interest rate explain more than half of the variance of output growth on average across countries.

Figure 9: Economic responses to a 1% (of GDP) credit impulse shock (2012-2019)



Note: The lines in figure 9 are the estimated impulse responses to a 1 percent of Chinese GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 1 for the VAR specification.

VIX and a depreciation of the broad real dollar, consistent with lower global risk aversion. Similarly, we find strong and significant positive effects on the S&P500 stock market index, pointing to an increase in global sentiment. These sentiment effects in turn reverberate into the financial system as we find positive and notable spillovers to the global credit markets. To the best of our knowledge, this is the first paper that formally shows China's notable contribution to the global financial cycle.

All told, we find that China's economy does not only has a significant contribution to the global business cycle but we find strong evidence that China's credit policies since the GFC have been an important driver of the global financial cycle.

5.3 The role of China and the U.S. in the global financial cycle

How do these effects compare to the role of the Unites States in driving the global financial cycle? While a direct comparison is extremely difficult given the special nature of China's credit policies, we compare our quantitative effects to the global financial effects from a 25 basis points decrease in the federal funds rate using the the methodology from Miranda-Agrippino and Rey (2020). Figure 10 shows that a 25 basis points decrease in the federal funds rate has significant positive spillovers to the global financial cycle as global domestic credit rises notably. In comparison to figure 9, we find that the effects of a credit impulse shock of one percentage point of Chinese GDP leads to positive spillovers to global domestic credit about the size of one third of a 25 basis points easing of U.S. monetary policy, which is significant.

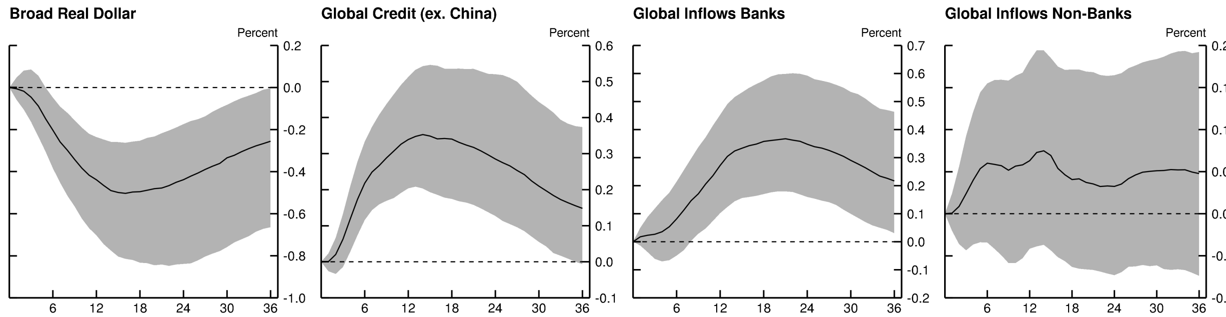
In addition, we find that the channels of financial spillovers from China's credit policies are somewhat different from those transmission channels in the United States. Indeed, as documented in Miranda-Agrippino et al. (2020), U.S. monetary expansions are followed by a significant leveraging increase of global financial intermediaries, a decline in aggregate risk aversion, an expansion in global asset prices and in global credit, a narrowing of corporate bond spreads, and a rise in gross capital flows. In China, however, we find that financial spillovers reverberate though the global financial system predominantly through sentiment effects. This decline in aggregate risk aversion in turn leads, which leads to expansion in global asset prices and in global credit.

5.4 Importance of China's alternative GDP

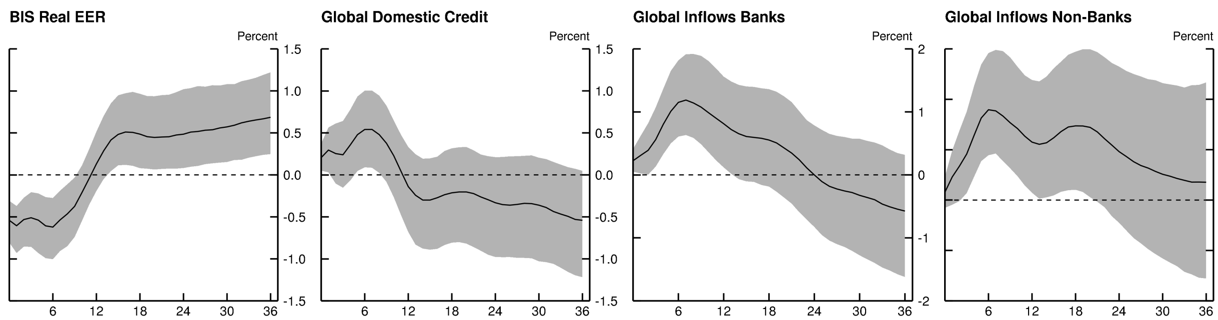
Next, we assess the importance of using China's alternative GDP in the VAR estimation. To that end, we estimate the same VAR as our baseline but include real official GDP instead of our alternative GDP measure. Given that China's official real GDP is released at the quarterly frequency, we first transform China's official real GDP to a monthly level using a monthly interpolation of the quarterly series. In the robustness section, we use monthly China's industrial production, which also exhibits this smoothness property in recent years.

Figure 11 presents the impulse response functions of an unexpected one standard deviation shock to China's credit impulse. What the result show is the China's expansionary credit policies do not have a significant impact on Chinese GDP, which is counter intuitive. In contrast, we do still find a positive and significant effect on global business activity. Indeed, global industrial production

Figure 10: Country comparison of contribution to the global financial cycle



(a) 1% (of GDP) Chinese credit impulse shock



(b) 25 basis points U.S. monetary policy shock (Miranda-Agrippino and Rey, 2020)

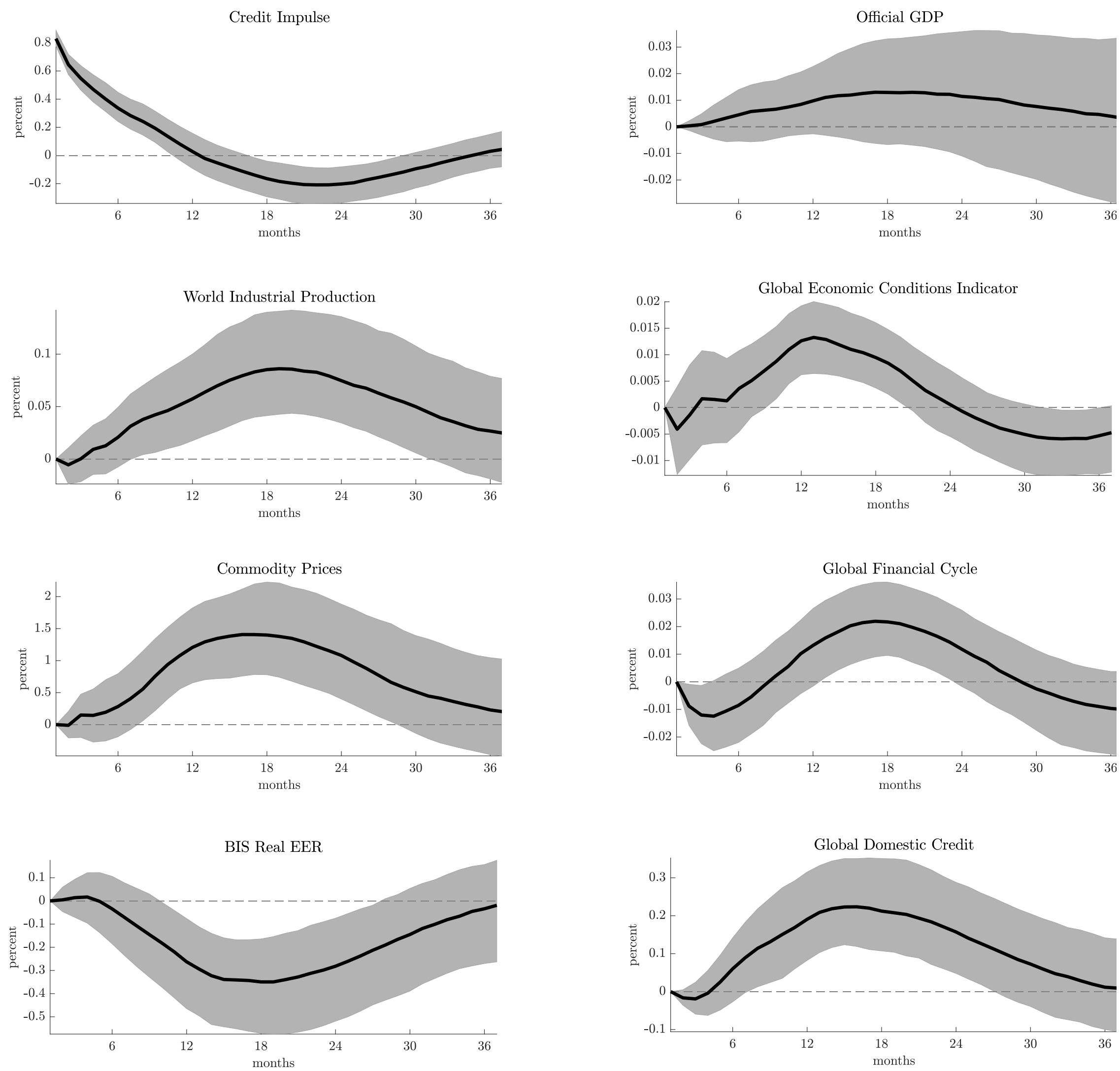
Note: Panels (a) and (b) in figure 10 compare the effects of a 1 percent of Chinese GDP shock to China's credit impulse to those from a 25 basis points decrease in the federal funds rate using the the methodology from Miranda-Agrippino and Rey (2020), respectively. The lines correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to October 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution.

excluding China increases in the medium run with the largest positive effects after 18 months. Similarly, we find a significant positive effect on commodity prices after 16 months.

Moreover, we also find that China's credit policies have a notable effect on the global financial cycle with a positive effect on global inflows into banks and global domestic credit.

All told, we find that our baseline VAR estimation with China's official real GDP masks the transmission from Chinese demand shocks, as proxied by the credit impulse, to the rest of the world. Indeed, while we still find significant spillovers to the global business and financial cycle, we find no effect of China's expansionary credit policies on China's economy. This result underscores the issue of using China's official real GDP in estimating the transmission to the global cycle as it has become overly smooth in recent years.

Figure 11: Economic responses to a credit impulse shock with official Chinese real GDP (2012-2019)



Note: The lines in figure 11 are the estimated impulse responses to 1 percent of GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution.

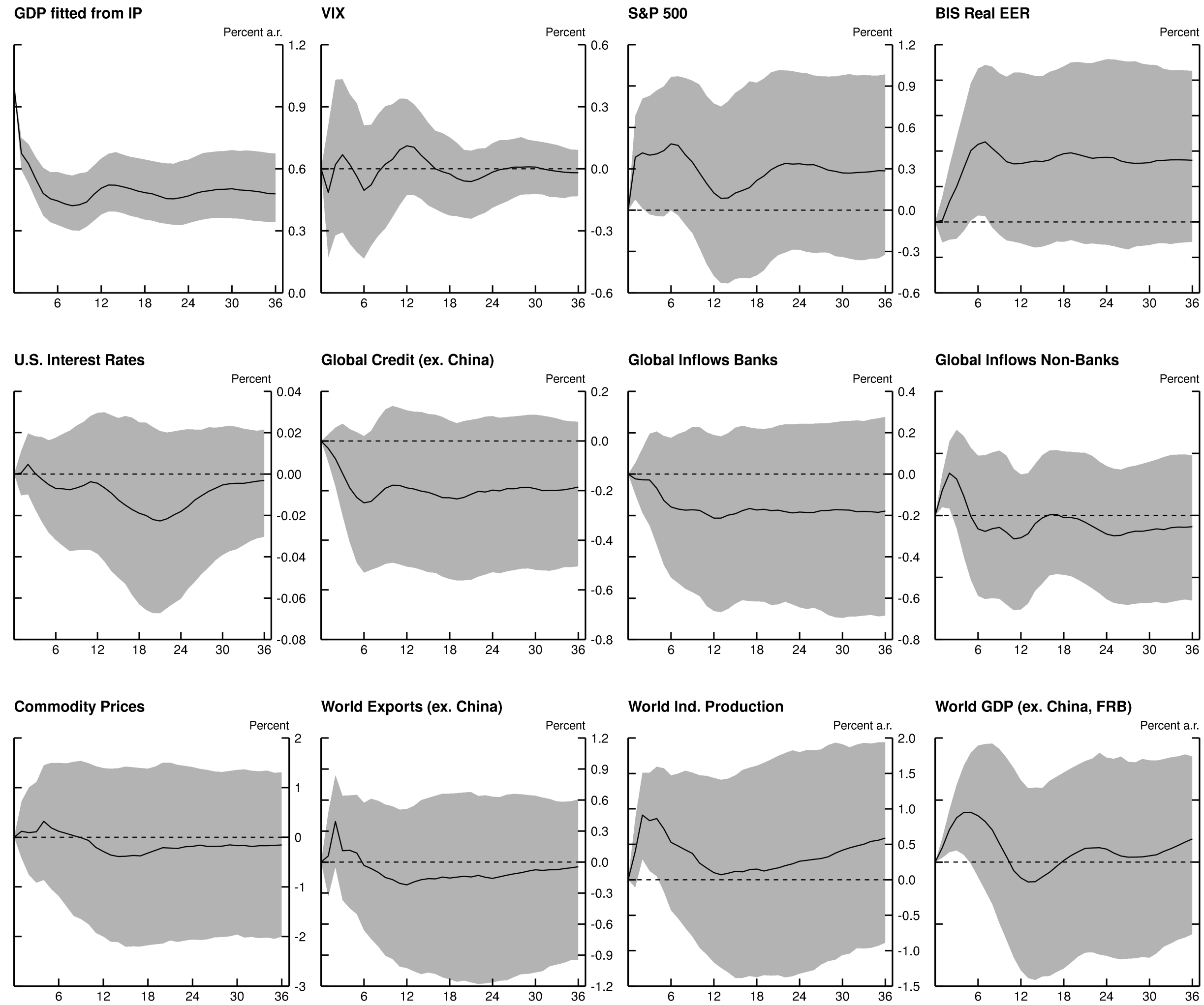
5.5 Importance of China's credit impulse

Next, we assess the importance of identifying Chinese demand shocks through our constructed credit impulse for China. As highlighted earlier, previous research focused on using shocks to Chinese real GDP to study the spillovers from China's economy to the rest of the world. However, using shocks to Chinese real GDP can confound Chinese demand and supply shocks. Therefore, to assess the importance of using China's credit impulse to identify Chinese demand shocks, we compare our results to a VAR model without China's credit impulse and our alternative real GDP growth measure for China. Specifically, we estimate a VAR with all the same global variables as in **??** but we include China's official real GDP and assess the spillovers of a shock to China's GDP to the rest of the world. Similar to our baseline approach, we assume that all variables can react with a one-month lag.

Figure 12 presents the impulse response functions. We find that an unexpected one standard deviation shock to China's official real GDP positively and significantly increases global industrial production excluding China with the strongest effects reached after 12 months. However, we no longer find an effect on commodity prices. In addition, we find that a shock to China's real GDP has no significant effect on the global financial cycle indicators. We do find a small significant impact on global inflows into banks but relatively short-lived of less than 6 months. Finally, we find no significant impact on global risk aversion as proxied by the real broad U.S. dollar. Altogether, we find that the Chinese economy has limited spillovers to the global cycle when using direct shocks to Chinese official real GDP.

To summarize, our results highlights that (1) identifying shocks that originate from China using the Chinese credit impulse and (2) using an alternative GDP measure for China's economy are both crucial to quantify the contribution of China's economy to the global business and financial cycle. We find that without addressing these two key issues, the spillovers from China to the rest of the world are mostly confined to real activity, albeit limited, with a very limited contribution to the global financial cycle. As such, China's contribution to the global cycle is hidden.

Figure 12: Economic responses to China's official real GDP shock (2012-2019)



Note: The lines in figure 12 are the estimated impulse responses to a one standard deviation shock to China's real official GDP and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 1 for the VAR specification.

6 Robustness

We perform several robustness exercises. We first explore how sensitive our main results are to different model specifications. Next, we explore different VAR specifications.

6.1 China's alternative growth specification

In this section we test the sensitivity of our alternative growth series for China. We estimate three additional alternative models to proxy for Chinese growth. The first alternative model we estimate uses the series used in Fernald et al. (2021). The second alternative model we estimate uses the series that market participants place the highest weight on according to Bloomberg. We include this model to be even more agnostic about which series to use. The third alternative model we estimate is the same as the benchmark model but exclude industrial production and retail sales as these series are highly correlated with official real GDP.[12] We use the same method to estimate our alternative growth measure as we used for our preferred model. We first present results for the different models estimated from 2000 on and then for 2012 on.

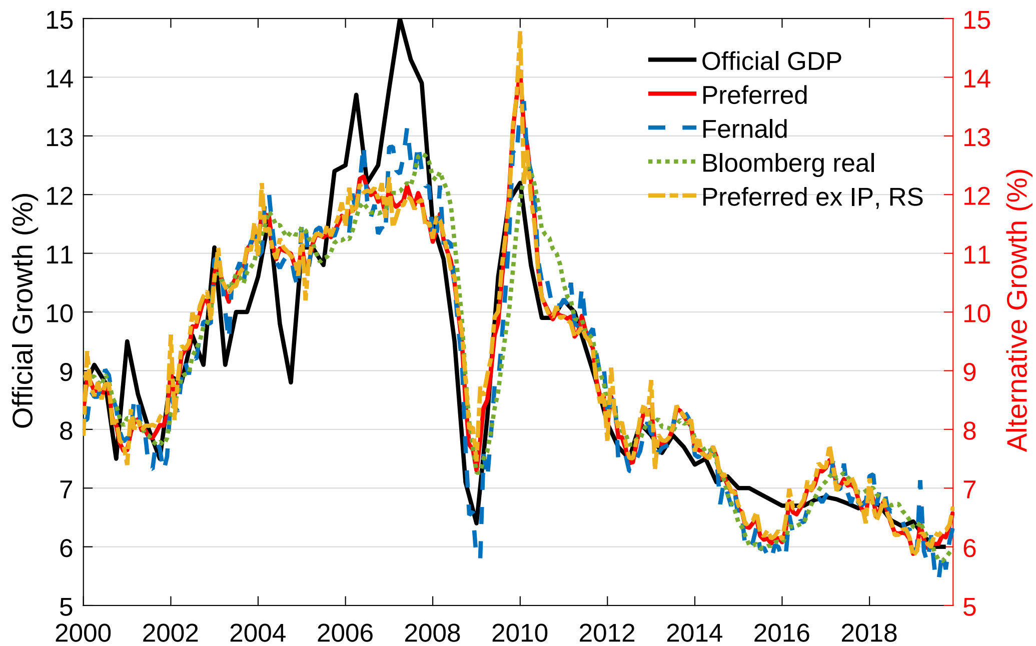
Figure 13 presents the model comparisons for the different DFMs estimated from 2000 on. The chart highlights that all alternative models show a very similar pattern. All alternative series do not pick up the variation in the real GDP growth in the period before the GFC. They do capture the large drop in economic growth and subsequent recovery during the GFC episode. Interestingly, all alternative series find a similar pattern in recent years. They all show a stronger downturn in the 2014-2015 'China scare' episode and a stronger upturn in the subsequent stimulus period. All told, we find that all models estimated from 2000 on show a similar patterns. Looking at the individual weights the DFM places on each of the underlying series, we find that this similarity is in large part driven by the relative large weight the DFM places on Chinese exports. However, as we documented earlier, China's economy has shifted from a production to a more consumption based economy in recent years. Indeed, China's dependence on exports has declined notably after the GFC.[13] As such, we compare all models when estimated from 2011 on.

Figure 14 presents the model comparisons for the different DFM estimated from 2011 on. Our preferred model shows the same volatility we estimated from 2000 on in recent years. We find a stronger downturn in the 2015 episode and a stronger upturn in the subsequent stimulus. In contrast, the Fernald et al. (2020) model does not show the same volatility as our preferred model. It shows a more muted 2015 downturn and subsequent upturn. Additionally, the model shows that estimated growth has been more or less in line with official growth since 2018. Therefore, it does not show the sharper-than-reported slowdown from the end of 2017 on our preferred model shows.

[12]See table A.1 in the appendix for the exact model specifications.

[13]Figure A.2 in the appendix plots Chinese gross and value added exports as a share of GDP. We highlight China's export dependence has declined since the GFC.

Figure 13: Alternative versus Official Growth

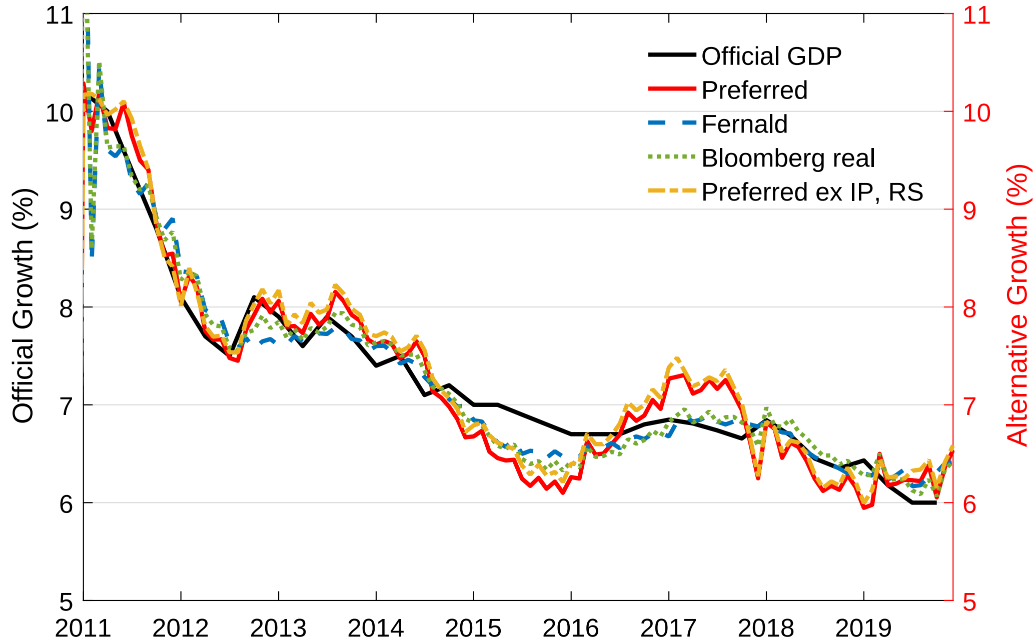


Note: Figure 13 plots China's official real GDP in 4-quarter changes. It plots the 12-month changes for several alternative Chinese GDP series estimated from 2000 to 2019: (1) our preffered model; (2) the Fernald et al. (2021) model; (3) the Bloomberg model, (4) Bloomberg model with real data only, and (5) our preferred model without industrial production (IP) and retail sales (RS).

Similar to the Fernald et al. (2020) model, the Bloomberg indicator model is less volatile compared to our preferred model when estimated from 2011.

All told, the models overlap relatively well in the early period. However, from 2015 we see a notable divergence where our model estimates a higher upturn and consecutive downturn compared to the other models. The reason behind this divergence is the inclusion of the underlying series. the majority of the data series in the Fernald et al. (2020) and Bloomberg real indicator model is tilted towards the manufacturing sector, whereas our preferred model also includes numerous services series. We find that the 2015 downturn was predominantly concentrated in the manufacturing sector, which is why the downturns capture similar movements across models. In contrast, the 2017 upturn was more concentrated in the services sector, which is not captured well by the other two models. Therefore, our preferred model seems to better capture the more recent volatility in Chinese GDP.

Figure 14: Model Comparison - Estimated from 2011 to 2019



Note: Figure 14 plots China's official real GDP in 4-quarter changes. It plots the 12-month changes for several alternative Chinese GDP series estimated from 2011 to 2019: (1) our preffered model; (2) the Fernald et al. (2021) model; (3) the Bloomberg model, (4) Bloomberg model with real data only, and (5) our preferred model without industrial production (IP) and retail sales (RS).

6.2 VAR Specifications

In this subsection, we explore the sensitivity of our main results to different VAR specifications. The different models are outlined in table 2.

6.2.1 Additional Chinese real GDP specifications

Chinese imports We first estimate a monthly VAR with the same variables as our main specification, but use Chinese imports instead of our estimated alternative growth measure as Fernald et al. (2021) argues that Chinese imports is correlated with Chinese GDP growth. However, given data concerns regarding Chinese reported imports[14], Fernald et al. (2021) use total foreign reported exports to China and Hong Kong. We follow the same methodology and substitute our alternative measure for Chinese official real GDP with Chinese imports. We estimate our model from 2012 to 2019. Similar to our main model, we identify a credit impulse shock through a recursive Cholesky decomposition in a block exogeneity structure, where the credit impulse is ordered last. As such, an exogenous credit impulse shock can affect China and the rest of the world with one-month lag.

[14]In particular, there are concerns regarding underreporting of Chinese imports

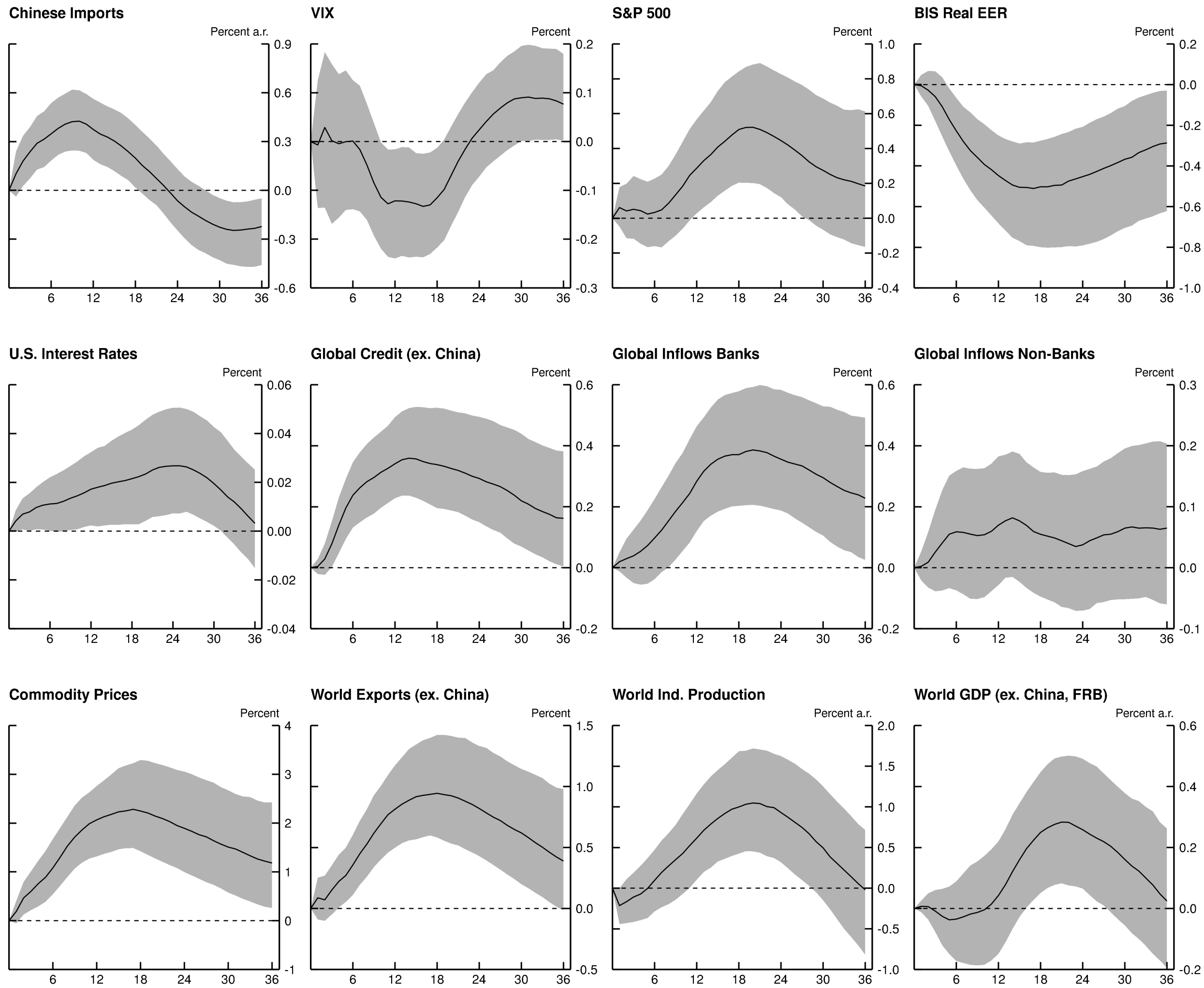
Table 2: VAR Variables - Robustness

Variable name	Source	Model		
		(5)	(6)	(7)
China's credit impulse	Own calculation	x	x	
Chinese imports	Own calculation	x		
Chinese IP	NBS		x	x
VIX	Haver	x	x	x
S&P500 index	Haver	x	x	x
Broad U.S. dollar	BIS*	x	x	x
2-year U.S. Treasury yield	FRB	x	x	x
Global domestic credit	BIS*	x	x	x
Global inflows to banks	BIS*	x	x	x
Global inflows to non-banks	BIS*	x	x	x
Commodity price index	Haver	x	x	x
Global Trade ex. China	Haver, Own calculation	x	x	x
Global IP ex. China	Haver, Own calculation	x	x	x
Global GDP ex. China	NBS*, Own calculation	x	x	x
Figures	2012-2019	15	16	17

Note: The top panel in table 2 lists the variables included in our robustness VAR model specifications. * denotes monthly interpolation of the quarterly original variables using a piecewise cubic interpolation. The bottom panel in table 2 describes the corresponding figures of each model estimation and for different time spans.

The impulse response functions are show in figure 15. We find that a one standard deviation shock to China's credit impulse significantly increases Chinese imports, with the strongest effects after 12 months and positive effects for about 24 months. We find the impulse response function to be very similar to the one for our alternative Chinese growth measure as highlighted in 9. We also find a lagged positive and significant effects on global industrial production outside of China with the strongest effects after 18 months. As such, this result highlights more direct evidence of the transmission channel. Indeed, the impulse response functions show that China's credit policies constitute an important driver of Chinese demand (imports) and consequently global industrial production. We also find positive effects on commodity prices in the medium run. Finally, we also find positive and significant effects on the global financial cycle again with a lag relative to the rise in Chinese imports. All told, we find that the positive effects of an unexpected shock to China's credit impulse are transmitted to the rest of the world as higher Chinese demand boosts global manufacturing. But the impulse responses also highlight that higher prospects for global growth diminishes global risk aversion (U.S. broad real exchange rate) and leads to an easing of global financial conditions.

Figure 15: Economic responses to a 1% (of GDP) credit impulse shock with Chinese Imports (2012-2019)



Note: The lines in figure 15 are the estimated impulse responses to a 1 percent of Chinese GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 2 for the VAR specification.

Chinese Industrial Production In section 5.4 we highlighted the importance of using our alternative GDP measure in our VAR estimation. Indeed, we show that an unexpected shock to China's credit impulse does not positively affect China's official real GDP, which is counter intuitive and reflects the fact that smoothness issue with China's real GDP. However, we interpolated China's real GDP from a quarterly to a monthly variable, which introduces some potential measurement error. Therefore, to underscore the same point, and as a robustness check, we use Chinese industrial production to proxy for real official Chinese GDP. As argued earlier, Chinese IP also exhibits this smoothness property in recent years.

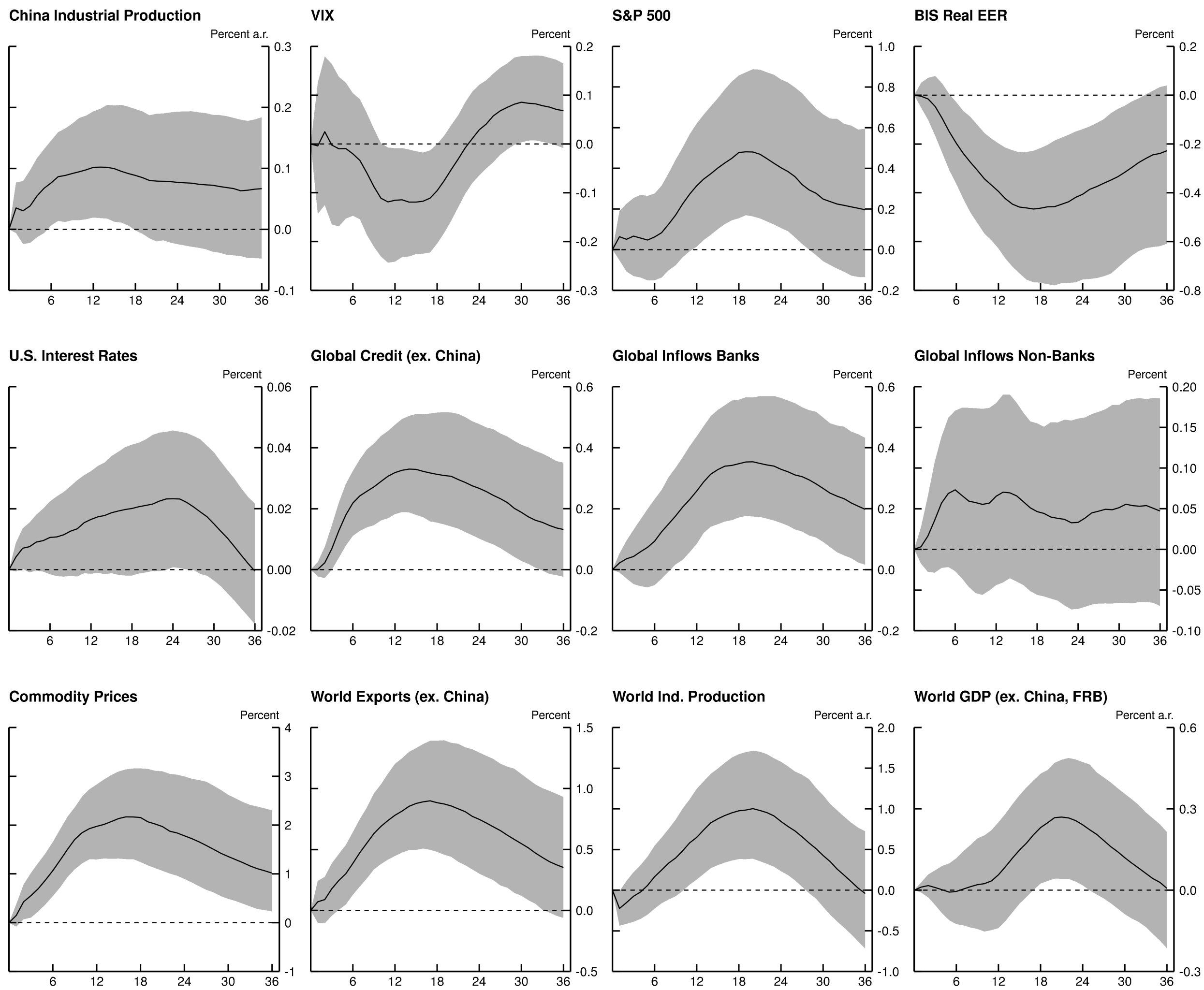
Figure 16 presents the results. The impulse response functions show that an unexpected shock to China's credit impulse leads to a positive but economically small effect on Chinese industrial production. Again, this result is counter intuitive as figure 16 also show that China's credit polices do have a positive and significant effect on global industrial production outside of China. Similarly, we find positive and significant effect on commodity prices and the global financial cycle. Therefore, these results are very similar to the previous results using China's official real GDP. All told, we find that using China's industrial production in our VAR estimation masks the impact China's credit policies have on its own economy. Therefore, this again underscores the importance of using an alternative growth measure.

6.2.2 Chinese demand shock specifications

Similar to the analysis in section 5.5 we assess the importance of using China's credit impulse to identify Chinese demand shocks in order to study China's contribution to the global cycle. To do so, we estimate a VAR where we use a one standard deviation shock to China's industrial production, similar to the analysis in figure 12, to estimate the spillovers to the rest of the world.

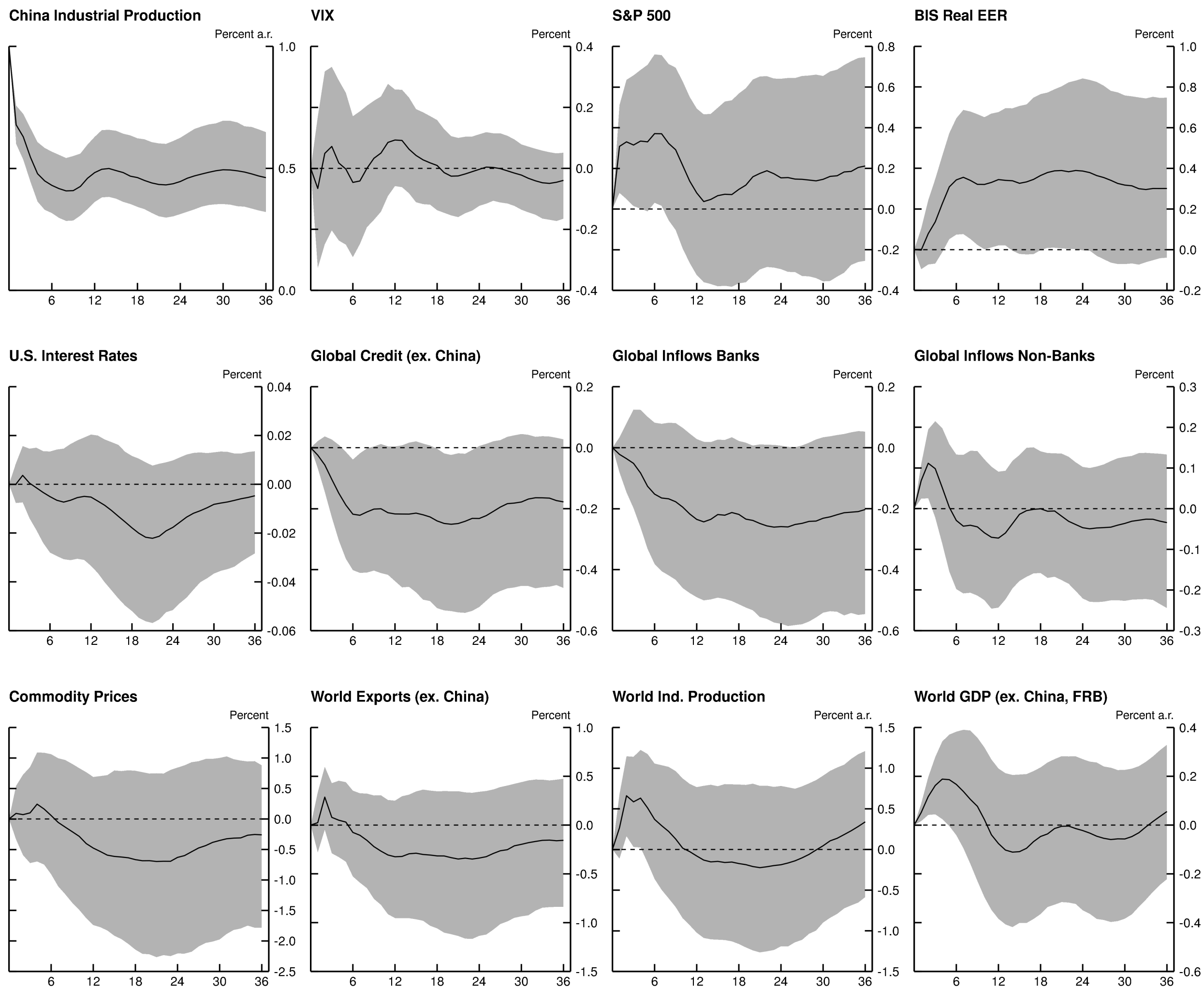
The results are presented in figure 17. The impulse response functions show that a one standard deviation shock to Chinese IP does not significantly affect global industrial production outside of China. Similarly, we find no significant effect on the global economic conditions index. Turning to financial variables, we find no significant spillovers to commodity prices, the global financial cycle, and global domestic credit. Moreover, we find that a shock to Chinese IP does not have a significant impact on the U.S. dollar. All told, these result are very similar to those presented in figure 12 where China is estimated to have limited spillovers to the rest of the world. Again, this highlights the issue with Chinese IP, which exhibits a similar smoothness property as official real GDP.

Figure 16: Economic responses to a 1% (of GDP) credit impulse shock with Chinese IP (2012-2019)



Note: The lines in figure 16 are the estimated impulse responses to a 1 percent of Chinese GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 2 for the VAR specification.

Figure 17: Economic responses to a 1 std. dev. shock to China's IP (2012-2019)



Note: The lines in figure 17 are the estimated impulse responses to a 1 standard deviation shock to China's official industrial production and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2012 to December 2019. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution. See table 2 for the VAR specification.

7 Conclusion

China's economy has grown rapidly over the past decades and has transformed the global landscape with it. Whereas China represented a small fraction of global GDP and global trade in the 1990s, it now accounts for 16 percent of world GDP and more than 30 percent of global growth. Yet, China's role as a major engine of global growth has been largely unexplored, potentially driven by the observation that its official GDP is seemingly uncorrelated with the global cycle. In this paper, we quantify the role of China's economy in driving the global cycle. Specifically, we estimate the impact of China's credit policies on global economic activity, commodity prices and global financial conditions. To do so, we first construct China's credit impulse, which aggregates different credit measures the Chinese authorities employ. Next, we construct an alternative growth series for China that better captures the volatility of underlying Chinese economic activity. Finally, we estimate a Structural Vector Autoregressive Model (VAR) to estimate the impact of movements in Chinese economic activity induced by China's domestic credit stimulus or tightening on economic activity in the rest of the world. Our results show that China has become an important driver of the global business and financial cycle since the Great Financial Crisis. Specifically, we find that China's expansionary credit policies lead to positive and significant increases in our alternative China's growth measure, commodity prices and global industrial production outside of China, highlighting that China's credit policies since have played an important role in supporting economic growth, not only in China but also globally. Moreover, we show that China's expansionary credit policies have a positive and significant effect on the global financial cycle.

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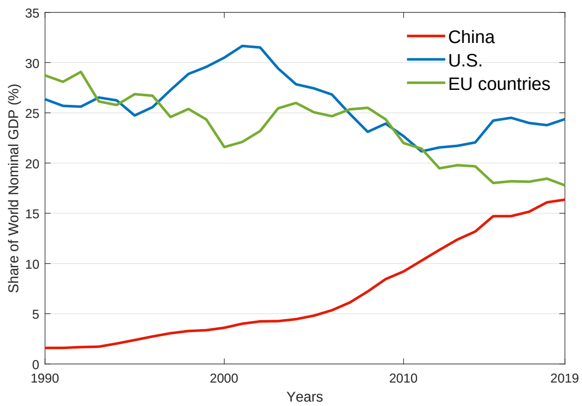
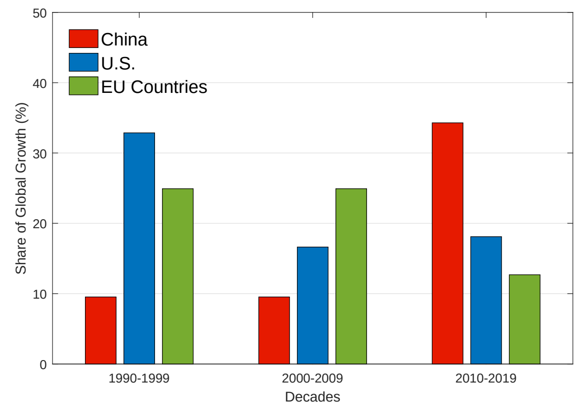
A Appendix

A.1 China's footprint in the global economy

Figure A.1: China's footprint in the global economy



(a) Share of global GDP (%)

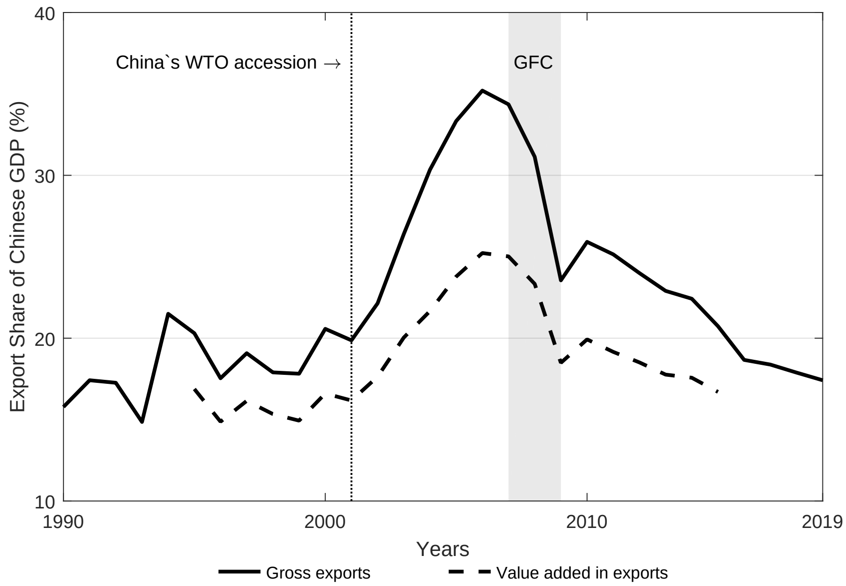


(b) Share of global growth (%)

Note: The left panel in figure A.1 plots the time series of nominal GDP as a share of global nominal GDP for China, the United States, and the European Union. The right panel plots the contribution to global nominal growth for each decade since 1990.

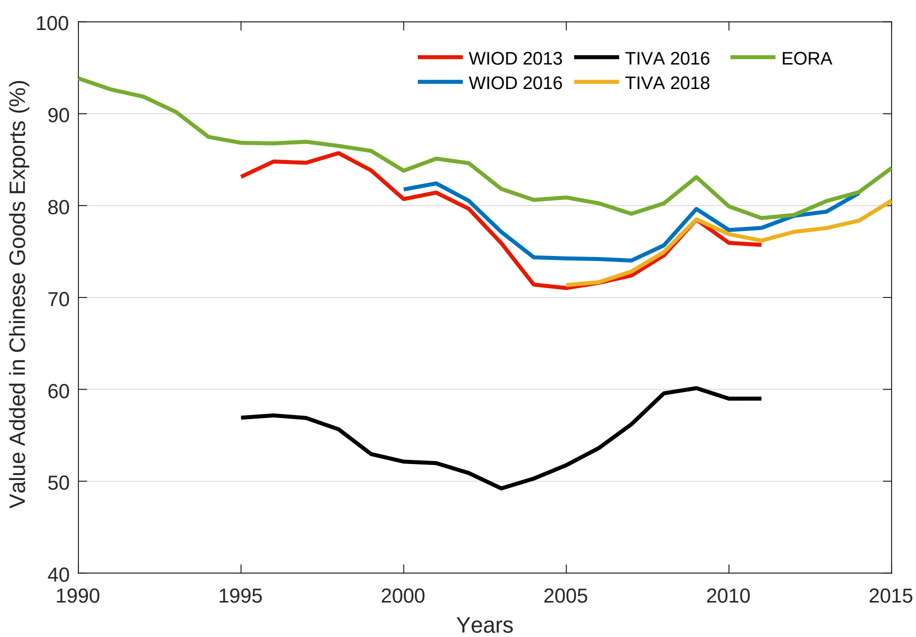
A.2 Chinese growth has become less export dependent

Figure A.2: Export share of GDP (%)



Note: The solid line in figure A.2 plots Chinese exports as a share of its nominal GDP. The dashed line plots the value added in Chinese exports as a share of its nominal GDP.

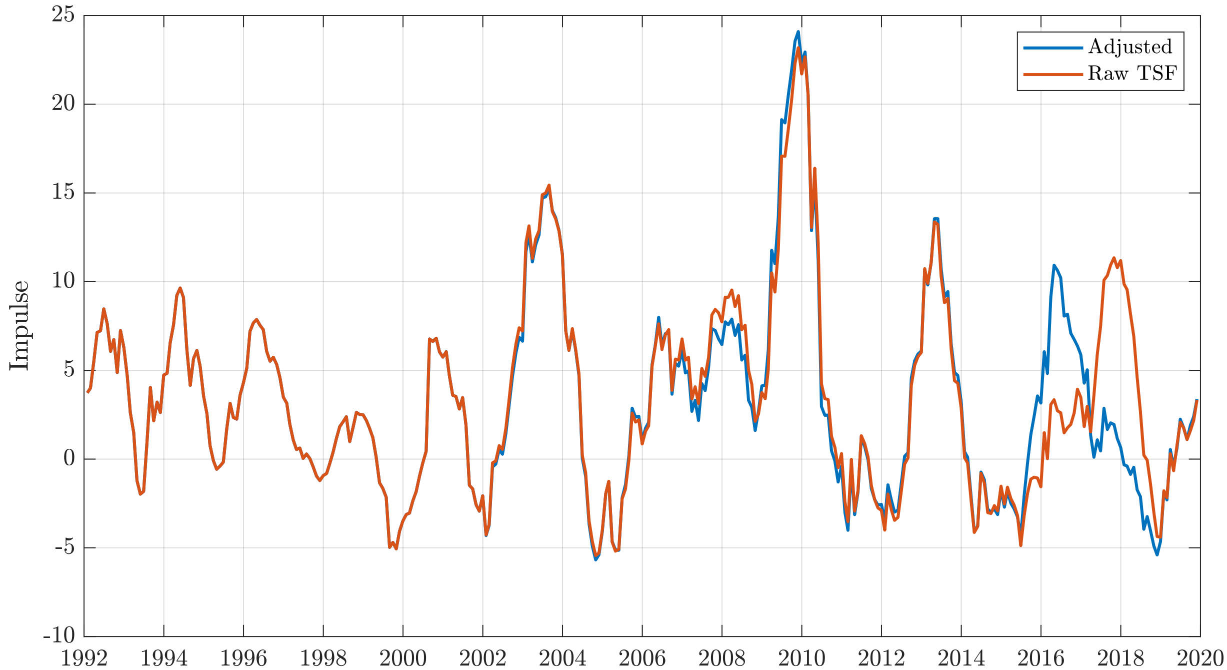
Figure A.3: Value Added in Chinese Exports - Different sources (%)



Note: Figure A.3 plot the time series of Chinese value added as a share of its total exports using different data sources including the world input-output database from 2013 and 2016, the trade in value added database from 2016 and 2018, and the EORA database.

A.3 China's credit impulse

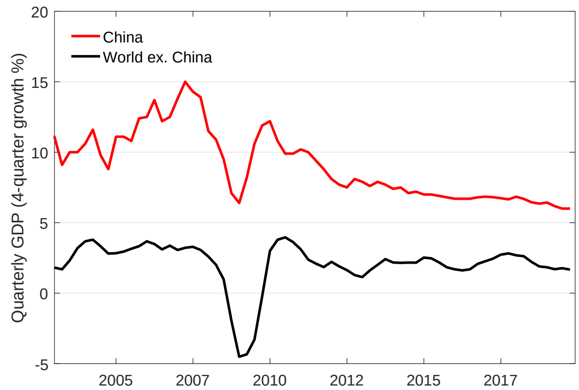
Figure A.4: China's credit impulse versus Total Social Financing (TSF) credit impulse (%)



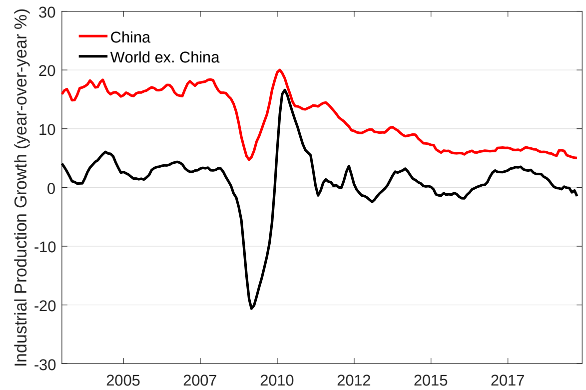
Note: Figure A.4 plots China's credit impulse based on total social financing (TSF) data and our preferred measure for China's credit impulse as the TSF measure adjusted for local and special local government bonds.

A.4 China's co-movement with the global cycle

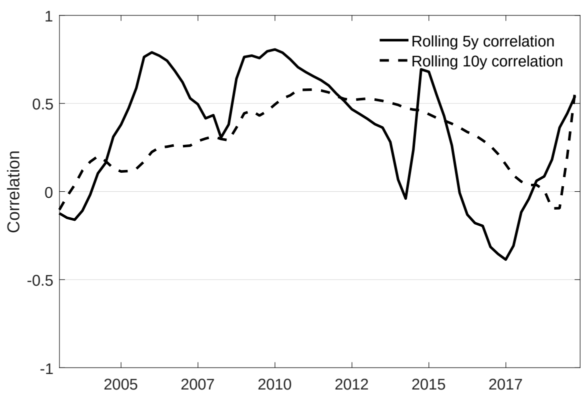
Figure A.5: China's economy and the global cycle



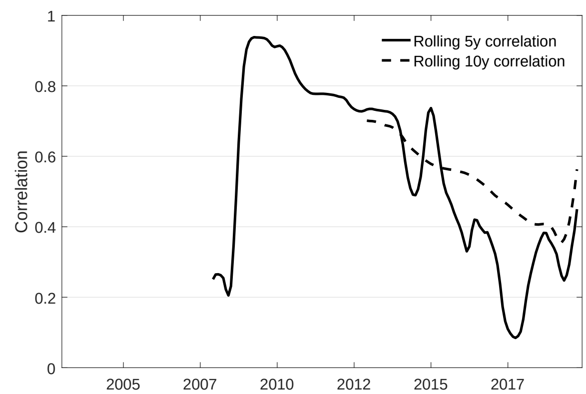
(a) Real GDP growth (%)



(b) Industrial production growth (%)



(c) Real GDP growth correlation

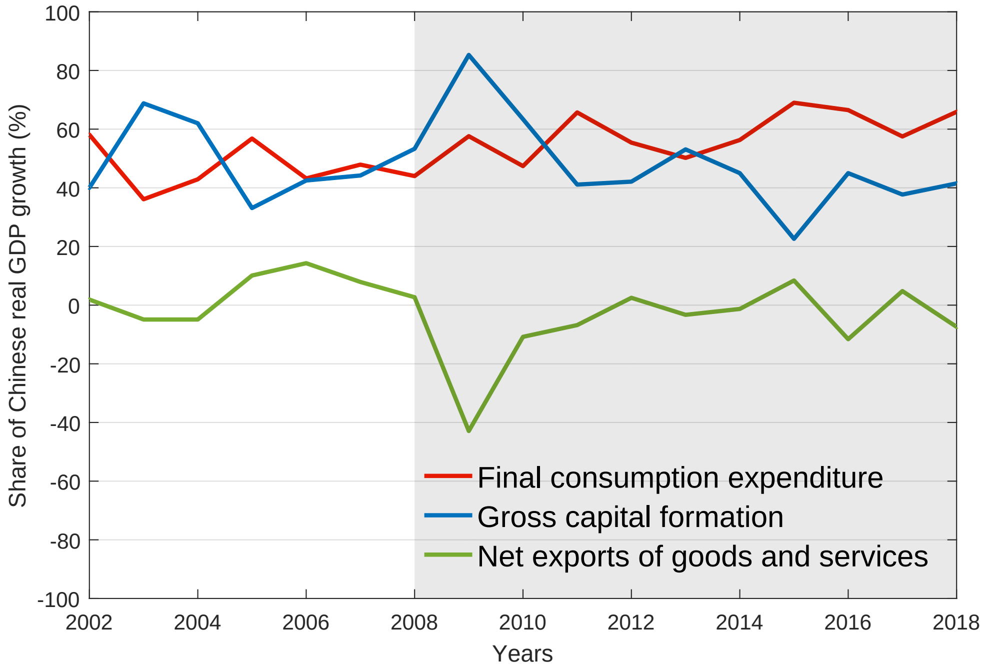


(d) Industrial production growth correlation

Note: Panels (a) and (b) in figure A.5 plot real GDP growth in 4-quarter changes and industrial production growth in 12-month changes, respectively, for China and the rest of the world. Panel (c) plots the rolling 5-year and 10-year correlation between real GDP growth of China and that of the rest of the world. Panel (d) plots the rolling 5-year and 10-year correlation between industrial production growth of China and that of the rest of the world.

A.5 Decomposition of China's official GDP - Demand side components

Figure A.6: China's demand side shares of real GDP growth (%)

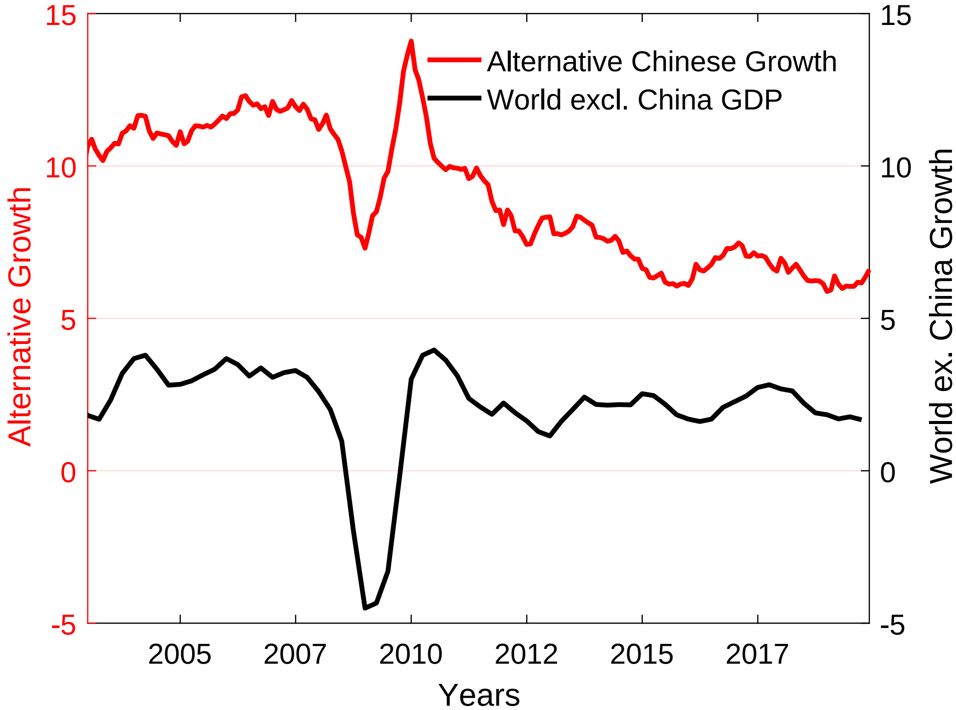


Note: Figure A.6 plots the time series of the demand side components of China's GDP, including final consumption, gross capital formation and net exports of goods and services, as contributions to Chinese real GDP growth.

A.6 Model Specification and Comparison

Figure A.7 presents our preferred model alternative Chinese growth estimate and world excluding China GDP growth.

Figure A.7: Alternative growth versus the global cycle



Note: Figure A.7 plots our preferred alternative Chinese GDP measure and global GDP outside of China in 12-month changes.

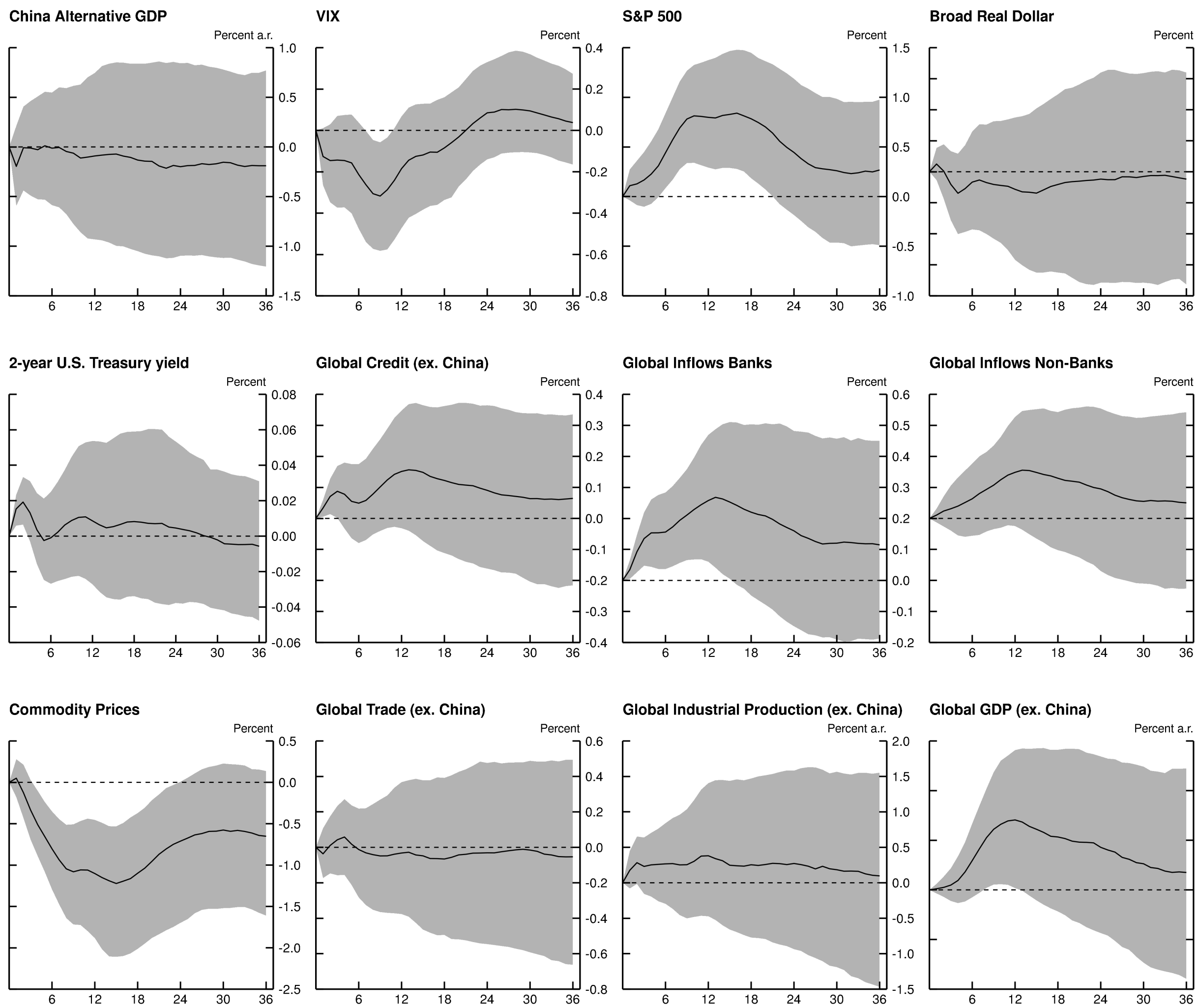
Table A.1: Model Specifications

Indicators	Source	Frequency	Preferred	Fernald et al. (2020)	Bloomberg
Industrial production	CEIC	month	x	x	x
Retail sales	CEIC	month	x	x	x
Fixed asset investment	CEIC	month		x	x
Fixed asset investment (manuf.)	CEIC	month	x		
Fixed asset investment (serv.)	CEIC	month	x		
Real estate investment	CEIC	month	x		x
Consumer expectation index	CEIC	month	x	x	
Electricity consumption	CEIC	month	x	x	
Electricity production	CEIC	month	x		
Chinese exports	CEIC	month	x	x	x
Chinese imports	CEIC	month			x
Chinese imports (foreign reported)	Haver	month	x		
Floor space started	CEIC	month	x	x	
Floor space sold	CEIC	month	x		
Railway freight	CEIC	month	x	x	
Cement production	CEIC	month	x		
Auto sales	CEIC	month	x		
Household items production	CEIC	month	x		
Copper import volume	CEIC	month	x		
Microcomputer production	CEIC	month	x		
Semiconductor production	CEIC	month	x		
Steel production	CEIC	month	x		
Ali Baba sales	Ali Baba	quarter	x		
Lenovo sales	Lenovo	quarter	x		
Tencent sales	Tencent	quarter	x		
Excavator sales	CEIC	month	x		
Copper import volume	CEIC	month	x		
Iron ore import volume	CEIC	month	x		
Caixin PMI (comp.)	CEIC	month			x
Caixin PMI (manuf.)	CEIC	month	x		x
Caixin PMI (serv.)	CEIC	month			x
Official PMI (comp.)	CEIC	month			x
Official PMI (manuf.)	CEIC	month			x
Official PMI (serv.)	CEIC	month			x
Satellite Nightlights	NOAA	month	x		
Nitrogen Dioxide (NO2)	TEMIS	month	x		
Official GDP	CEIC	month			x
Industrial profits	CEIC	month	x		x
Foreign direct investment	CEIC	month			x
New home prices	CEIC	month			x
TOTAL			31	8	16

Note: Table A.1 presents the underlying series that go into the DFM estimation of our preferred alternative growth model specification and additional models specifications

A.7 Additional VAR results

Figure A.8: Economic responses to a credit impulse shock (2001-2007)



Note: The lines in figure **??** are the estimated impulse responses to a 1 percent of Chinese GDP shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR estimated from January 2001 to December 2007. The grey shaded area represents the one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior distribution.