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# What Happens in China Does Not Stay in China*

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**Abstract**

Spillovers from China to global financial markets have been found to be small owing to China's limited integration in the global financial system. In this paper, however, we provide evidence that China constitutes an important driver of the global financial cycle. We argue that because of China's importance for global consumption, stronger Chinese growth raises global growth prospects, inducing an increase in global risk sentiment and an expansion in global asset prices and global credit. Two contributions are key to this finding: (1) We construct a measure of China's credit impulse to identify Chinese policy-induced demand shocks. Our approach takes advantage of the fact that a primary tool of China's stabilization policy—encompassing monetary, fiscal, and regulatory policies—is controlling the amount of credit in the economy. Without China's credit impulse, it is difficult to discern global financial spillovers; (2) We estimate an alternative measure of Chinese GDP growth that captures its business cycle given data concerns about the smoothness of official GDP data. Without China's alternative GDP measure, it is difficult to attribute any global cycle movements to economic developments in China.

**JEL classification:** C52, E50, F44
**Keywords:** China, Growth, Credit Impulse, Global Financial Cycle, Global Business Cycle, Global Risk Sentiment, Commodity Prices

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# 1 Introduction

We provide evidence that China is an important driver of the global financial cycle–the global common movement of capital flows, risky asset prices, credit growth, and leverage (Rey, 2013). This is in contrast to previous studies, which have found small spillovers from China to global financial conditions owing to China's limited integration in the global financial system (Arslanalp et al., 2016; Miranda-Agrippino et al., 2020). We argue that despite China's limited financial integration, spillovers from China reverberate through the global financial system through sentiment effects due to its importance as a driver of global business activity. China's economy is the second largest in the world and accounts for more than a third of global growth. Moreover, China represents a significant source of global consumption. For example, in 2021, China accounted for about 40% of global vehicle sales, almost double the size of those in the United States, and 25% of global smartphone sales, making it the largest smartphone market. In addition, China is a big consumer of commodities, accounting for around 50% of global steel and coal demand, and 14% of global oil demand. In this paper, we formally show that China constitutes an important driver of the global business cycle as fluctuations in Chinese demand affect global goods and commodity trade. As such, higher economic growth in China raises global growth prospects, inducing a decline in aggregate risk aversion, proxied by the VIX–the 30-day option-implied volatility index of the S&P 500–, and an expansion in global asset prices and credit.

What greatly complicates the analysis to study spillovers from China to the rest of the world is that fluctuations in Chinese demand since the Global Financial Crisis (GFC) appear to not be reflected in official real GDP movements. Clark et al. (2020), Groen and Nattinger (2020), and Fernald et al. (2021) argue that Chinese official GDP has become overly smooth, especially in the decade following the GFC, and therefore masks underlying economic fluctuations. As a result, it is difficult to attribute any global cycle movements to economic developments in China. In addition, Chinese authorities use a multitude of policy instruments–blurring the lines between fiscal, monetary, and regulatory policies–to stimulate and cool the economy, making it complicated to assess the stance of policy based on any one policy instrument. We address both data challenges before estimating spillovers from China.

First, to isolate Chinese demand shocks, we take advantage of the fact that the Chinese authorities exert a significant degree of control over the supply of credit to the economy, with coordinated monetary, fiscal, and credit policies effectively treating credit supply as an intermediate policy target.

We construct a measure of China's credit impulse using different types of credit influenced by the Chinese authorities including bank loans, shadow credit, and local government bonds. We then use exogenous shocks to this impulse in an empirical model that accounts for the influence of global economic and financial developments on China, to evaluate the effects of Chinese policy-induced credit shocks on its economy and the transmission to the rest of the world.

Second, we construct an alternative measure of Chinese real GDP that relies on a large set of indicators that are informative about the Chinese business cycle, including property market data, auto sales, reported exports to China from other countries, satellite nighttime lights data, and pollution data (Chen et al., 2019; Morris and Zhang, 2019; Clark et al., 2020; Groen and Nattinger, 2020; Fernald et al., 2021).[1] We extract a common factor from these series using a dynamic factor model (DFM), which has become an important tool for tracking high-frequency economic activity, and use this common factor to construct an alternative measure of Chinese real GDP.

After addressing the main data challenges, we quantify the effects of China's credit policies on the global financial cycle. We do so by estimating a monthly Bayesian vector autoregression (VAR) that includes variables capturing the overall state of global financial conditions, global business activity, and China's economic activity. The results from our VAR show that China constitutes an important driver of the global financial cycle as unexpected policy-induced changes in Chinese domestic credit have significant effects on both global credit conditions and global economic activity. Next, we evaluate the transmission channels. Our results show that Chinese credit shocks lead to a rise in global risk sentiment, proxied by the VIX, which increases global asset prices and credit. To the best of our knowledge, this is the first paper that formally shows that China's credit policies are an important driver of the global financial cycle. This results might seem puzzling given that China does not have a big presence in global financial markets. We argue that its influence reverberates through the global financial system through its impact on global growth given China's importance in global consumption. Our results show that Chinese credit policies since the GFC have sizeable effects on global economic activity. We estimate that a policy-induced increase in China's credit impulse of 1% of GDP boosts its own economy by 1.2%. After one to two years, the credit shock is estimated to induce a 0.3% increase in global GDP outside of China and raise commodity prices and global trade excluding China by 2.2% and 1%, respectively, boosted by stronger Chinese demand. Our results highlight that expansionary credit policies in China affect global financial conditions through raising global risk sentiment as stronger Chinese consumption lifts global growth.

[1] Our constructed credit impulse and alternative GDP growth series are available for research purposes on our personal websites, along with the suggested citation.

Finally, we find that both of our contributions are important in capturing the effect of China's credit policies on its own economy and identifying the transmission to the rest of the world. Indeed, it is difficult to discern an impact of China's policy-induced demand shocks on the rest of the world without the credit impulse. If we follow the literature that uses shocks to China's real GDP to study global spillovers, the results show that China has almost no impact on the global financial cycle and only a small effect on the global business cycle. Similarly, 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. If we estimate our VAR with China's official GDP instead of our alternative measure, Chinese credit shocks do not significantly affect domestic output, which is puzzling and counter intuitive. We interpret this result as providing additional evidence that China's official GDP does not fully capture its business cycle movements. Moreover, this result also underscores the importance of our alternative GDP measure. Without it, it is difficult to attribute any global cycle movements to economic developments in China.

Our paper speaks to several streams of the global cycle literature. We contribute to an emerging literature that studies the global spillovers from China's economy (Dizioli et al., 2016; Furceri et al., 2017; Gauvin and Rebillard, 2018; Ahmed et al., 2019; Miranda-Agrippino et al., 2020; Clayton et al., 2022). To the best of our knowledge, this is the first paper that quantifies the role of Chinese demand shocks, measured by a comprehensive Chinese credit measure, to the global financial and business cycle using an alternative growth measure for China. Relative to previous studies that quantify China's spillovers to global business activity, 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 (EMEs). In contrast, we find that China's economy has significant spillovers to global GDP and not just EMEs, boosted by stronger Chinese demand. As such, we contribute to a large literature that studies the role of trade on global business cycle co-movements (Baxter and Kouparitsas, 2005; Kose and Yi, 2001; Calderon et al., 2007; Liao and Santacreu, 2015). Specifically, Johnson (2014), Duval et al. (2015), and de Soyres and Gaillard (2019, 2022) highlight the importance of trade in intermediate inputs as part of global value chains and its contribution to global GDP co-movements. Our results provide evidence that China's credit policies are an important driver of global business activity, as stronger Chinese demand raises global trade.

We also contribute to a large literature that studies the drivers behind the global financial cycle. Many studies have focused on the role of the United States. Bruno and Shin (2015a) Bruno and Shin (2015b), and Miranda-Agrippino and Rey (2020) have established the importance of U.S. monetary policy as one of the main drivers of the global financial cycle. 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. Boehm and Kroner (2021) finds evidence that U.S. business cycle news shocks are important drivers of the global financial cycle. We view our paper as shedding light on the importance of the second largest economy, China, as a relevant driver of the global financial cycle. As such, part of our paper is closely related to Miranda-Agrippino et al. (2020), which studies the global footprint of China's monetary policy. They use a monetary policy index based on Jia and Xu (2019)'s estimated natural interest rate as a proxy for the policy stance of the People's Bank of China (PBOC), China's central bank. In this paper, however, we consider a broader measure to identify policy-induced Chinese demand shocks. We follow this approach as we argue that China's unique institutional setup blurs the lines between fiscal, monetary, and regulatory policies. We focus on the supply of total domestic credit in the economy, which the Chinese authorities view as a key intermediate policy target. As in Miranda-Agrippino et al. (2020), our findings show that policy-induced Chinese demand shocks raise international trade and commodity prices. However, we also find that China's credit policies are 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 lower VIX, which elevates global asset prices and credit.

The remainder of the paper is organized as follows. Section 2 highlights several data challenges that arise in quantifying global spillovers from China. Section 3 details the estimation of China's alternative GDP series. Section 4 describes the quantitative analysis. Section 5 presents the main results. Section 6 compares global spillovers from China to those from the United States and quantifies how China's role in the global economy has evolved. In section 7, we perform several robustness exercises. Section 8 concludes.

## 2 Quantifying Spillovers from China: Data Challenges

We highlight several data challenges in quantifying spillovers from China to global financial and economic conditions, and how we address them.

We start with the challenge of identifying policy shocks in the Chinese context. First, China's unique institutional setup blurs the lines between fiscal, monetary, and regulatory policies, all of which are coordinated by the State Council, China's highest executive body. Indeed, Chinese authorities use a multitude of policy instruments to achieve their objectives, including many 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 loans 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 GFC has relied heavily on the use of off-budget quasi-government entities. As a result, it is difficult to assess the stance of policy based on any one policy instrument. 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, policy communications are generally constrained due to the presence of many stakeholders in Chinese policy decisions (McMahon et al., 2018). Therefore, an approach of constructing news-based measures over a narrow time frame to identify policy shocks, which has been used in other contexts (e.g., Gertler and Karadi, 2015; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021), is not well suited to identify Chinese policy shocks.

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 goal 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 et al., 2020). 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, an aim of monetary policy that continues to this day (Chen et al., 2018, 2020).

As such, movements in a comprehensive measure of total credit in the Chinese economy, if properly controlled for endogenous movements and other shocks, are informative about government-induced stabilization policies. Our preferred measure of the policy stance is the credit impulse, which measures the change in new credit in relation to GDP.[2] To construct a comprehensive measure of China's 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 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.[3] Therefore, we first augment the TSF measure from the PBOC to include local government bonds.[4] 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.[5] 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 the same change the year prior as a percent of nominal GDP. It is measured at the monthly frequency and is defined 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 new Chinese domestic credit in month $m$, and $Y_m$ is China's monthly official nominal GDP.[6]

Panel A in figure 1 illustrates the credit impulse as a share of China's GDP. It highlights that the Chinese authorities have long used credit to stabilize the economy as they have long faced a

[2]The credit impulse has increasingly become a closely watched metric of China's policy stance among investment banks.

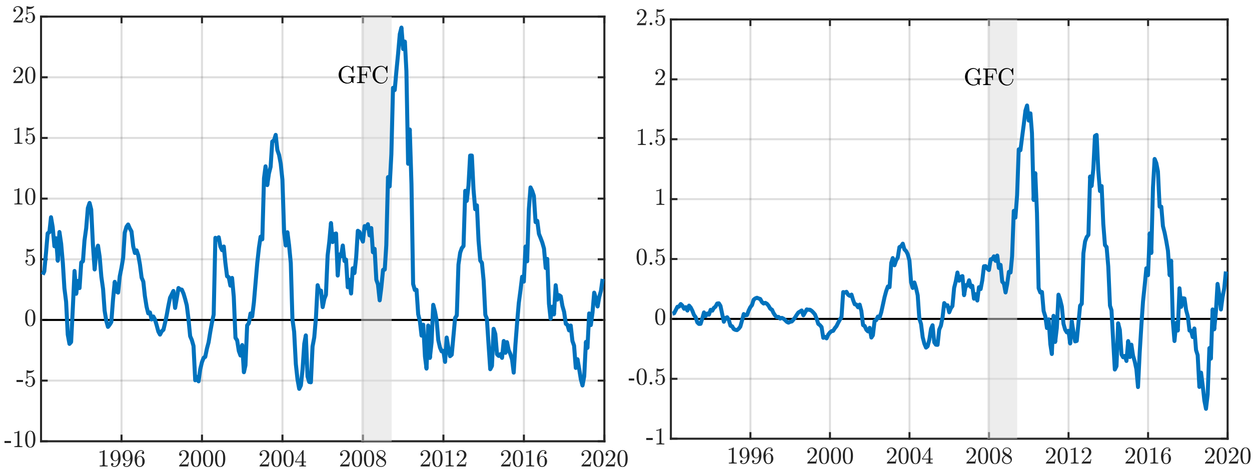
[3]In 2019, the TSF definition changed to include special local government bonds.

[4]Accounting for the usage of local government bonds in China is important to correctly measure China's credit impulse. Figure B.1 in appendix A plots the credit impulse without augmenting the Chinese TSF series with local government bonds. As figure B.1 highlights, Chinese authorities responded with substantial credit stimulus after the economic downturn in 2015, which was in large part driven by local government bond issuance. According to the TSF data, the stimulus period is identified incorrectly as starting only at the end of 2016.

[5]In the 1990s, renminbi denominated loans accounted for the bulk of domestic credit in China. The rise of shadow banking and local government bond issuance became quantitatively important after the GFC.

[6]We use nominal GDP to scale the inflow of new credit given that the credit series are nominal. As GDP is released at the quarterly frequency, we impute monthly GDP by dividing total quarterly GDP evenly over the three corresponding months.

tradeoff between strong economic growth and financial stability objectives. That said, the GFC stands out as a period of massive credit stimulus, amounting to 25% of GDP. To size China's credit measures in a global context, panel B in figure 1 illustrates China's credit impulse as a share of global GDP. It shows that prior to the GFC, China's credit measures represented a small share of global GDP. However, with China's rise in the global economy, the quantitative importance of China's credit policies has risen as well. Indeed, China's last three stimulus episodes each accounted for around 1.5% of global GDP.




Panel A: As a % of China's GDP

Panel B: As a % of Global GDP

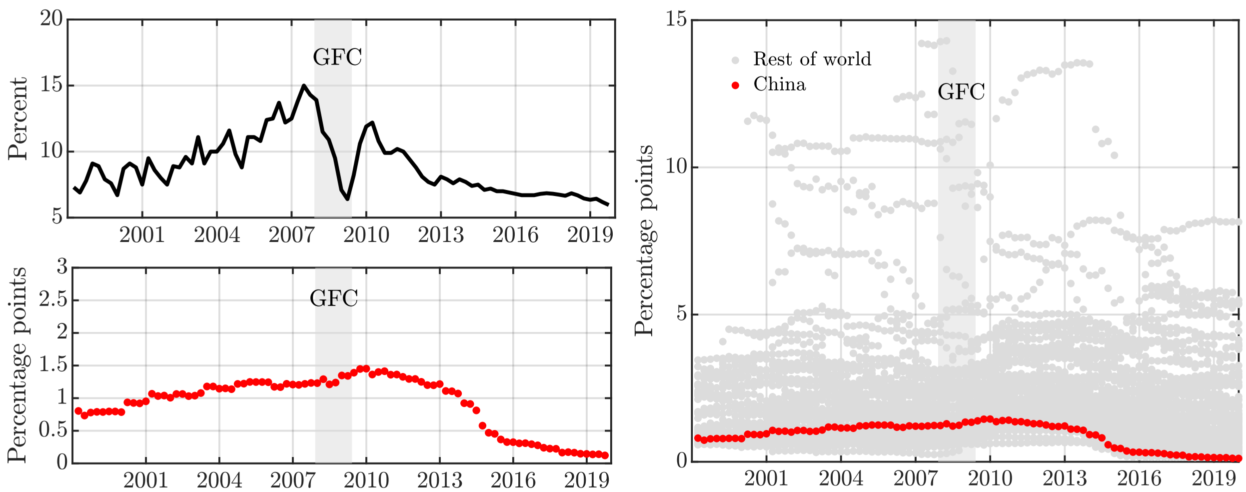
Figure 1: China's Credit Impulse

Note: China's credit impulse is calculated as the change in the flow of new credit in the past 12 months relative to those the year prior as a percent of China's nominal GDP (panel A) and global nominal GDP (panel B).

The second issue in quantifying China's role in driving global financial and economic conditions are concerns about the quality of China's GDP data. Concerns have been expressed that Chinese GDP data could be mismeasured (Rawski, 2001) and implausibly smooth (Nakamura et al., 2016), a problem that, according to some, has become more acute during the 2010's (Groen and Nattinger, 2020; Clark et al., 2020; Fernald et al., 2021). To underscore this point, panel A in figure 2 plots Chinese quarterly real GDP growth and the five-year moving standard deviation of its first difference over the past decades. It illustrates that the volatility of the first difference of China's GDP growth has fallen markedly in recent years. Panel B in figure 2 plots that same volatility for China and compares it to a large set of countries.[7] It illustrates that the volatility of changes in China's GDP growth has historically been among the smallest in the world. Additionally, that volatility has

[7]The full set of countries is detailed in appendix B.

fallen even further in the 2010s and is the lowest in all countries' history, suggesting that China's GDP might be overly smooth, especially in the past decade. Indeed, a formal test for a structural break in the historical volatility of China's GDP shows that the hypothesis of no structural break is consistently rejected in the last decade, with an estimated indicative break point in mid-2010.[8]




Panel A: China

Panel B: Cross-country

Figure 2: Real GDP Growth Volatility

Note: The top and bottom charts in panel A plot China's official real GDP growth in 4-quarter changes and the 5-year rolling standard deviation of its first difference, respectively. Panel B plots the 5-year rolling standard deviation of the first difference of real GDP growth in 4-quarter changes for China and 107 other countries.

All told, China's official GDP may be masking its underlying business cycle and, with that, the economic movements resulting from government-induced policy changes. As a result, it has become increasingly difficult to attribute any global cycle movements to economic developments in China. To address this concern, we estimate an alternative GDP measure for China.

# 3 Estimation of Alternative Chinese GDP

## 3.1 Dynamic Factor Model

We employ a dynamic factor model (DFM) to estimate an alternative real GDP growth series for China by taking signal from a a large panel of indicators that are informative about the Chinese business cycle. The ability of DFMs to summarize a large set of non-synchronous, disconnected

[8] We follow the methodology of McConnell and Perez-Quiros (2000) of recursively testing the null hypothesis of no structural break against the alternative of one break in GDP volatility. Details and results can be found in the mathematical appendix

data makes them an ideal tool for monitoring macroeconomic conditions in real time (Giannone et al., 2008). The idea 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 factors ($\boldsymbol{f}_t$). 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 sets of observation equations, defined as

$$\begin{bmatrix} \mathbf{y}_{m,t} \\ \mathbf{y}_{q,t} \end{bmatrix} = \begin{bmatrix} \mathbf{\Lambda}_m & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{\Lambda}_q & 2\mathbf{\Lambda}_q & 3\mathbf{\Lambda}_q & 2\mathbf{\Lambda}_q & \mathbf{\Lambda}_q \end{bmatrix} \begin{bmatrix} \boldsymbol{f}_t \\ \boldsymbol{f}_{t-1} \\ \boldsymbol{f}_{t-2} \\ \boldsymbol{f}_{t-3} \\ \boldsymbol{f}_{t-4} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{m,t} \\ \mathbf{e}_{q,t} \end{bmatrix}, \tag{2}$$

while factors are defined by the transition equations

$$\boldsymbol{f}_t = \mathbf{A}_1 \boldsymbol{f}_{t-1} + ... + \mathbf{A}_p \boldsymbol{f}_{t-p} + \mathbf{u}_t. \tag{3}$$

The observed variables $\mathbf{y}_{m,t}$ and $\mathbf{y}_{q,t}$ are vectors of $n_m$ monthly and $n_q$ quarterly data, respectively, while $\boldsymbol{f}_t$ 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 with their persistence modeled as an AR(1). We link the monthly growth rates to their quarterly counterparts using the aggregation procedure proposed by Mariano and Murasawa (2003). The matrices $\mathbf{\Lambda}_m$ and $\mathbf{\Lambda}_q$ are full, and so all monthly and quarterly variables load on all $r$ factors. The matrices $\mathbf{A}_1$ to $\mathbf{A}_p$ bring a VAR-like structure to the latent factors. We define our measure of alternative Chinese growth as a DFM projection with one factor, and $p = 1$ lag.

### 3.2 Data

In order to estimate the DFM, we need to include data series that capture underlying economic activity in China. In selecting these series, there are two key issues.

The first issue is that some key economic indicators, including industrial production and retail sales, are highly correlated with official GDP growth. And like official GDP, these series have also become markedly smoother during the 2010's.[9] We address this issue by taking an agnostic approach regarding those series that are potentially subject to the same smoothness concerns as official real GDP, and include those in the information set of our preferred DFM estimation.[10]

The second issue is that the structure of China's economy has shifted from one driven by investment and exports to a more consumption-based economy.[11] Therefore, our estimation needs to include data series that also reflect the consumption side of the economy. We do so by including series such as auto sales, property market sales, and series reflecting high-tech goods demand including semiconductor production and mobile phone production. While some of these series have relatively short time spans compared to industrial sector series, we can incorporate those in the estimation given that the DFM can accommodate series with different time horizons.

For our preferred model we use a combination of traditional Chinese series, Chinese series believed to better capture the Chinese business cycle, and series from non-Chinese agencies. Table B.1 specifies all underlying data series we use.

### 3.3 Alternative GDP Growth

We compute two alternative GDP growth measures, from 1999 to 2019 and from 2011 to 2019[12]. To estimate these growth series that are comparable to official growth, but recover China's underlying business cycle, we take the following steps:

1. Estimate the DFM with data in 12-month changes[13] and extract one global factor for each estimation.

2. Convert the global factor movements into GDP movements:

    - Regress the de-trended global factor on de-trended official real GDP growth in 4-quarter percent changes from 1999 to 2011.[14] The underlying assumption is that the alternative

[9] Chen et al. (2019) document additional data issues related to industrial production.

[10] As part of our robustness analysis in section 7, we exclude these series in the set of possible variables to let the DFM determine which series to place a higher weight on.

[11] See appendix A for more background on China's economy.

[12] We chose to end the estimation sample before the COVID-19 pandemic, which started in early 2020. The main reason is that this global recession was not driven by underlying economic conditions, but rather reflected a global health crisis. As a result, the VAR estimation to isolate China's contribution to the global financial and business cycle would be contaminated by the effects from the COVID-19 pandemic that do not necessarily reflect the effects of China's credit policies.

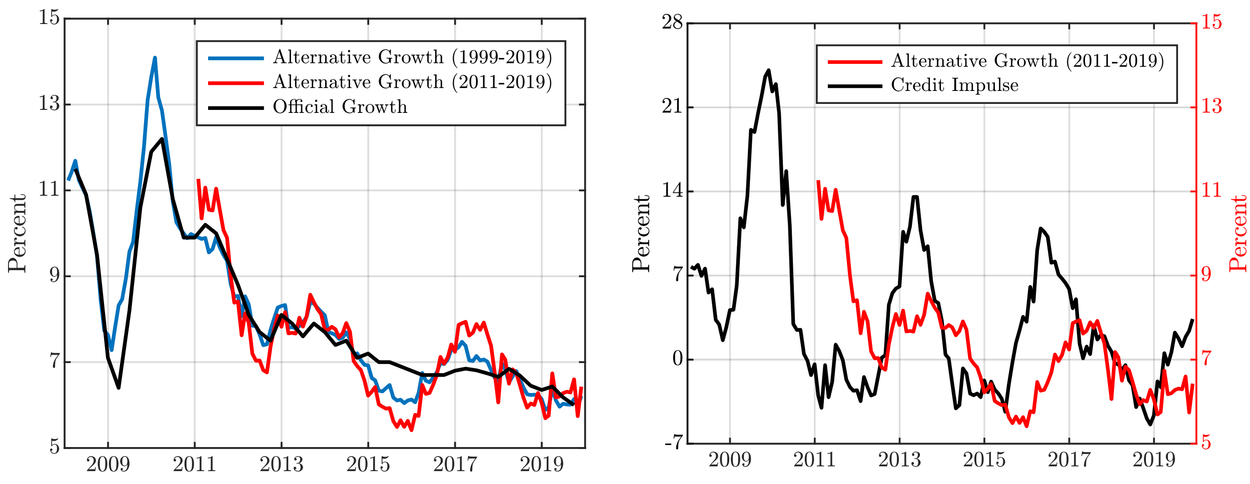
[13] We choose to estimate the DFM in 12-month changes to mitigate measurement error issues given that the majority of Chinese data series are reported in 12-month or year-to-date 12-month percent changes as opposed to typical level series. The exceptions include PMI series and the consumer confidence index, which are level series.

[14] Trend and cycle of GDP and the global factor are extracted using the Hodrick–Prescott filter.

data are informative about the growth cycle, but not about the growth trend. In addition, we estimate the elasticity for a shorter time horizon to address concerns about smoothness in official GDP data during 2010s.[15]

- Use the same elasticity to map movements of the global factor for each estimation into a de-trended monthly series of 12-month economic growth.
- Add back the trend of official real GDP growth. The underlying assumption is that official GDP is informative about the growth trend, but not about the cycle.

Panel A in figure 3 plots our two estimated alternative Chinese growth series, estimated from 1999 to 2019 and from 2011 to 2019, and compares them to officially reported growth. There are several takeaways. First, our alternative GDP growth measure estimated from 1999 to 2019 matches the GFC movements and the slowdown following the GFC relatively well. Second, in the later years of the 2010s, our estimated alternative growth is more volatile than official growth. Similarly, our alternative GDP growth measure estimated from 2011 to 2019 is more volatile in the later years of the 2010s compared to official GDP growth.[16]




PANEL A: VERSUS OFFICIAL GROWTH

PANEL B: VERSUS CREDIT IMPULSE

FIGURE 3: ESTIMATED CHINESE ALTERNATIVE REAL GDP GROWTH

Note: Panel A plots China's official real GDP growth in 4-quarter changes and our two alternative Chinese GDP growth measures, estimated for 1999-2019 and 2011-2019, in 12-month changes. Panel B plots China's credit impulse and our alternative Chinese GDP growth, estimated from 2011-2019, in 12-month changes.

[15] More specifically, we restrict the time horizon for the estimation of de-trended GDP on the de-trended global factor to exclude the time period for which official GDP data are less informative about China's growth cycle.

[16] In section 7, we further explore the difference in volatility also between our two alternative GDP growth measures.

In particular, two periods of a cyclical downturns stand out as not appearing in official GDP data. Our alternative growth indicators suggests that the 2015 economic slowdown in China was more pronounced than officially reported. Similarly, our alternative growth measures suggest that there was a cyclical downturn in 2018 even though that is not apparent in official GDP data. All told, our estimated alternative growth series suggest that China's business cycle is much more pronounced than officially reported especially in the later years of the 2010s.

The impact of credit policies is more apparent when we compare our alternative measures of economic growth to the credit impulse, as highlighted in panel B in figure 3. This is particularly striking because we have not included any credit measures in our DFM estimation. Even so, the credit impulse appears to lead our alternative growth indicators, suggesting that China's credit policies may indeed be a an important source of its business cycle movements.

### 3.4 Alternative GDP Level

A major challenge faced by the literature on alternative growth models for China, is the transformation from a 12-month growth series to a level series because there is no GDP level series that is uniquely identified from the 12-month growth rates. Moreover, its estimation is further complicated by the non-linearity implied by the 12-month compounding of the unobserved monthly series. We provide a methodological contribution to the aforementioned literature by transforming our alternative 12-month GDP series into a monthly GDP level, which is key for our VAR estimation. We propose a method to extract underlying month-to-month growth rates from 12-month growth rates, and use those to construct a level series for 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. Following their notation, let $Y_t$ represent 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 $Y_t^*$ relate as follows:

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

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

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

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

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

Defining $y_t = \log Y_t - \log Y_{t-12} = \Delta_{12} \log Y_t$ as the growth rate of the quarter 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

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

or simply

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

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

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

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.[17] We construct the monthly growth version of our alternative GDP ($y_t^*$) by estimating the state-space model 9, taking signal from our 12-month alternative growth rate ($y_t$).

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, a series in 12-month growth rates exacerbates the approximation error as it accumulates 12 monthly rates instead of only three in the case of quarterly growth rates. Second, China's annual GDP growth ranges from 6 to 12% in recent years, which implies that monthly changes are not small. We address these issues 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[18]

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

Such a transformation implies an adjusted monthly growth rate $\tilde{y}_t^*$ defined as

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

which we use to construct our alternative GDP level series for China.[19]

# 4 Quantitative Analysis

After addressing the main data challenges, we quantify the effects of China's credit policies on the global financial cycle. We estimate a monthly Bayesian VAR in levels that includes variables

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

[18] We estimate $x$ as 2.40, which is slightly smaller than Euler's number.

[19] Figure B.2 presents the imputed monthly GDP growth rates, $y_t$, estimated from the state-space model 9 and the adjusted GDP growth rates, $\tilde{y}_t^*$, as computed by equation 12, which are used to estimate our Chinese alternative GDP level series.

capturing the overall state of global financial conditions, global business activity, and China's economic activity. We then evaluate the transmission effects of unexpected policy-induced changes in Chinese credit. As previously highlighted, we opt for a shock to the credit impulse as Chinese authorities exert a significant degree of direct control over the supply of credit to the economy, allowing us to identify demand shocks that originate from China. This approach is preferred to directly estimating the impact of Chinese GDP on global activity as shocks to China's GDP confound supply and demand shocks.

We identify a credit impulse shock through a recursive Cholesky decomposition in a block exogeneity structure, where the credit impulse is ordered last after all the indicators, including China's alternative GDP. Formally, take a vector of endogenous variables $\mathbf{y}_t$ with moving average representation (in levels) as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{13}$$

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

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t, \tag{14}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{15}$$

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. It follows that the policy function for the credit impulse (CI) implied by this identification, or the last equation of the VAR, can be represented as

$$CI_t = \underbrace{\mathbf{B}_{1,n}\mathbf{y}_{t-1} + ... + \mathbf{B}_{1,n}\mathbf{y}_{t-p}}_{\text{Endogenous response to economic developments}} + \underbrace{\sum_{i=1}^{n-1} a_{i,n}\mathbf{s}_{i,t}}_{\text{Endogenous response to global and China's shocks}} + \underbrace{a_{n,n}\mathbf{s}_{n,t}}_{\text{Policy-induced credit shock}}, \tag{16}$$

which implies that the credit impulse reacts endogenously to global economic and financial developments, to economic developments arising in China, and to economic shocks arising in the rest of the world and in China. Credit impulse movements that are not endogenously explained by these developments are the exogenous credit impulse shock, representing the government-induced discretionary credit policies. This structure also implies that the credit impulse shock cannot affect the rest of the world and China contemporaneously, but rather with a one-month lag. We estimate Bayesian VARs with 12 lags and an intercept term by taking advantage of Minnesota priors (Litterman, 1986; Bańbura et al., 2010) to address the large number of coefficients. Coverage bands for the impulse responses are computed using 1,000 draws from the posterior distribution.

Table 1 describes the variables we include in our different VAR specifications. For the estimation of our main VAR models, we focus on the period after the GFC when China's footprint in the global economy is largest. As a result, we use our alternative GDP measure estimated from 2011 to 2019 as the time period corresponds.[20]

Table 1: VAR Model Specifications

| 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 | | |
| Official Chinese real GDP | NBS* | | | x | x |
| Global financial cycle | Miranda-Agrippino and Rey (2020) | x | | | |
| Global economic conditions | Baumeister et al. (2022) | x | | | |
| VIX | Haver | | x | x | x |
| S&P 500 | 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 |
| Figures | | 4 | 5 | 6 | 7 |

Note: The top panel lists the variables included in the different VAR model specifications. † The alternative Chinese real GDP growth measure is estimated from January 2011 to December 2019. The NBS is the National Bureau of Statistics in China. * denotes monthly interpolation of the quarterly variables using a piecewise cubic interpolation. The bottom panel describes the corresponding figures for each model estimation.

[20] We re-estimate our benchmark model in appendix C with our alternative GDP measure estimated from 1999 to 2019 and show that our results are robust to our GDP specification. That said, we find that the effect of China's credit policies on its own economy is dampened somewhat.

# 5 Results

We first estimate a narrow VAR to capture China's contribution to the global financial and business cycle measured by aggregate indexes. Then, we estimate an extended VAR to study the transmission channels of China's credit policies to the rest of the world. Finally, we highlight the importance China's credit impulse to identify policy-induced Chinese demand shocks and the importance of our alternative Chinese GDP measure.

## 5.1 Narrow Model

We first estimate a four-variable VAR (model 1 in table 1) to analyze the contribution of Chinese policy-induced credit policies to the global financial cycle measure as constructed by Miranda-Agrippino and Rey (2020), and to the global business cycle, as measured by the global economic conditions index constructed by Baumeister et al. (2022). The reason why we estimate this narrow model is to focus on global cycle aggregates, thereby reducing the number of parameters estimated, especially given the relatively short time horizon. We focus on a period after the GFC when China's footprint in the global economy is largest.[21]

Figure 4 presents the impulse response functions and also plots their 16$^{\text{th}}$ and 84$^{\text{th}}$ percentiles for the draws from the posterior distribution. We find that a policy-induced increase in China's credit impulse of 1% of GDP leads to a significant rise in our alternative growth measure of Chinese GDP, and the positive effects are strongest around 16 months after the shock.

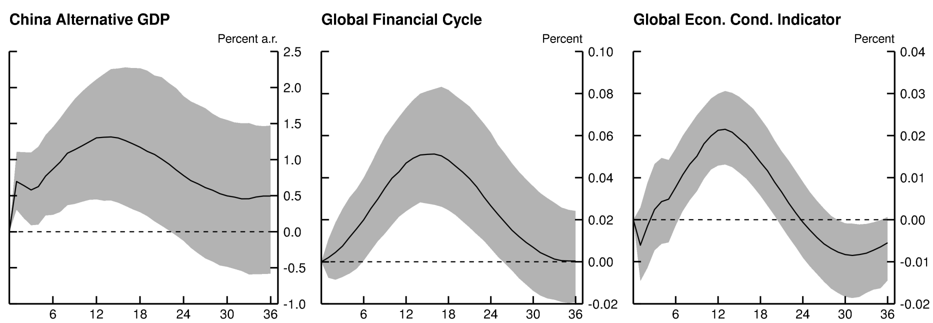



Figure 4: Impulse Responses to a Chinese Credit Impulse Shock

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock and correspond to the posterior median estimates. The VAR is estimated from January 2011 to April 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.

[21] The estimation period is January 2011 to April 2019. The published global financial cycle measure goes through April 2019, which restricts the end of the sample period.

Turning to spillover effects, figure 4 highlights that a positive shock to China's credit impulse notably eases global financial conditions. The impulse response function shows a positive and significant impact on the global financial cycle indicator. Interestingly, the effects are strongest after about 16 months and, therefore, lag the positive effects on Chinese GDP, pointing to a transmission from China's economy to the rest of the world, and not vice-versa. A policy-induced credit expansion also positively and significantly affects the global economic conditions index. Again, 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 from China to the rest of the world.

All told, the results from our narrow model show that changes in Chinese credit conditions since the GFC have had significant effects on both global credit conditions and global economic activity. Moreover, the IRFs show that the transmission occurs from China's economy to the rest of world.

### 5.2 Benchmark Model

Next, we estimate an extended VAR with disaggregated data that allow us to study the channels of transmission to the rest of the world in more detail given that the narrow model only includes aggregated measures.[22] Our benchmark VAR includes 13 endogenous variables as described in table 1 (model 2) and is estimated from January 2011 to December 2019.[23] Figure 5 presents the impulse responses after an unexpected, policy-induced credit impulse shock of 1% percent of Chinese GDP.

First, we consider the effects of China's expansive credit policies on the Chinese economy using our alternative GDP measure. We find that a positive shock to China's credit policies of 1% percent of Chinese GDP leads to a 1.2% rise in China's alternative GDP measure. The impulse response functions show that the strongest effects on China's GDP occur after 16 months with significant positive effects for just under 24 months. This result highlights that China's credit policies constitute an important driver of fluctuations in Chinese GDP.

Next, we study the effects on global financial conditions. Figure 5 illustrates that China's expansive credit policies lead to an increase in global credit outside of China of 0.4%. Moreover, we find a positive and significant rise in global inflows into banks of 0.4%. The effects are strongest after about 18 months and therefore, lag the positive effects on Chinese GDP, which points to the transmission from China's economy to the rest of the world, and not vice-versa. Our results show that China's expansionary credit policies and the subsequent increase in China's economic

[22]Moreover, the narrow model may suffer from omitted variables bias, as we have not included more direct transmission measures.

[23]With the exception of the 2-year U.S. Treasury yield and the credit impulse, all variables are level series.

growth reverberates through the global financial system by affecting global economic sentiment. As illustrated in figure 5, a positive credit impulse shock is estimated to decrease aggregate risk aversion, associated with a lower VIX, which pushes up global asset prices. We also find a notable 0.5% depreciation of the broad U.S. dollar, triggered by the decrease in global risk aversion. These sentiment effects in turn reverberate through the global financial system and increase global credit. All told, we provide evidence that China's credit policies since the GFC have had notable spillovers to global financial markets. This result might be somewhat surprising given that China does not have a big presence in global financial markets and its financial system is relatively closed off to global investors. This begs the question of what drives the spillovers from China to global financial fluctuations if not through direct financial linkages.

To answer the question of why China matters for the global financial cycle, we consider the spillovers effects from China on global economic activity. Figure 5 shows that a positive shock to China's credit impulse of 1% of Chinese GDP induces an increase in global industrial production and global GDP excluding China of about 1% and 0.3%, respectively. In addition, the rise in our estimated measure for Chinese growth–peaking at around 16 months–leads the upswing in industrial production and global GDP outside of China, which peak at around 22 months. This lagged response indicates that the real economic effects are also transmitted from China to the rest of the world. Specifically, we find that China's expansionary credit policies spill over to global real activity through international trade linkages. Indeed, a positive shock to China's credit impulse of 1% of Chinese GDP induces an increase in global trade outside of China of about 1%, underscoring quantitatively strong Chinese demand spillovers.[24] Moreover, we find that stronger Chinese demand leads to an increase in commodity prices of 2.2%.[25] As such, expansionary credit policies in China not only raise growth prospects in China but globally given China's significant role in global consumption, thereby lifting global risk sentiment. Finally, we find that as the Chinese and the global economy heat up, the United States reacts by tightening monetary policy, with a positive and significant effect on the 2-year U.S. Treasury yield after two years.

Our results show that the spillovers from credit policies in China to global financial markets occur with a lag. This delayed response might be somewhat surprising given that financial markets are forward-looking. We interpret the lagged response to likely reflect two main issues. The first

[24] Figure 11 in the robustness analysis provides more direct evidence of China's expansionary credit policies leading to higher Chinese demand, proxied by imports.

[25] This result is complementary to Fernández et al. (2020), in that we formally identify China as an important driver of commodity price movements in the period after the GFC. They 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.

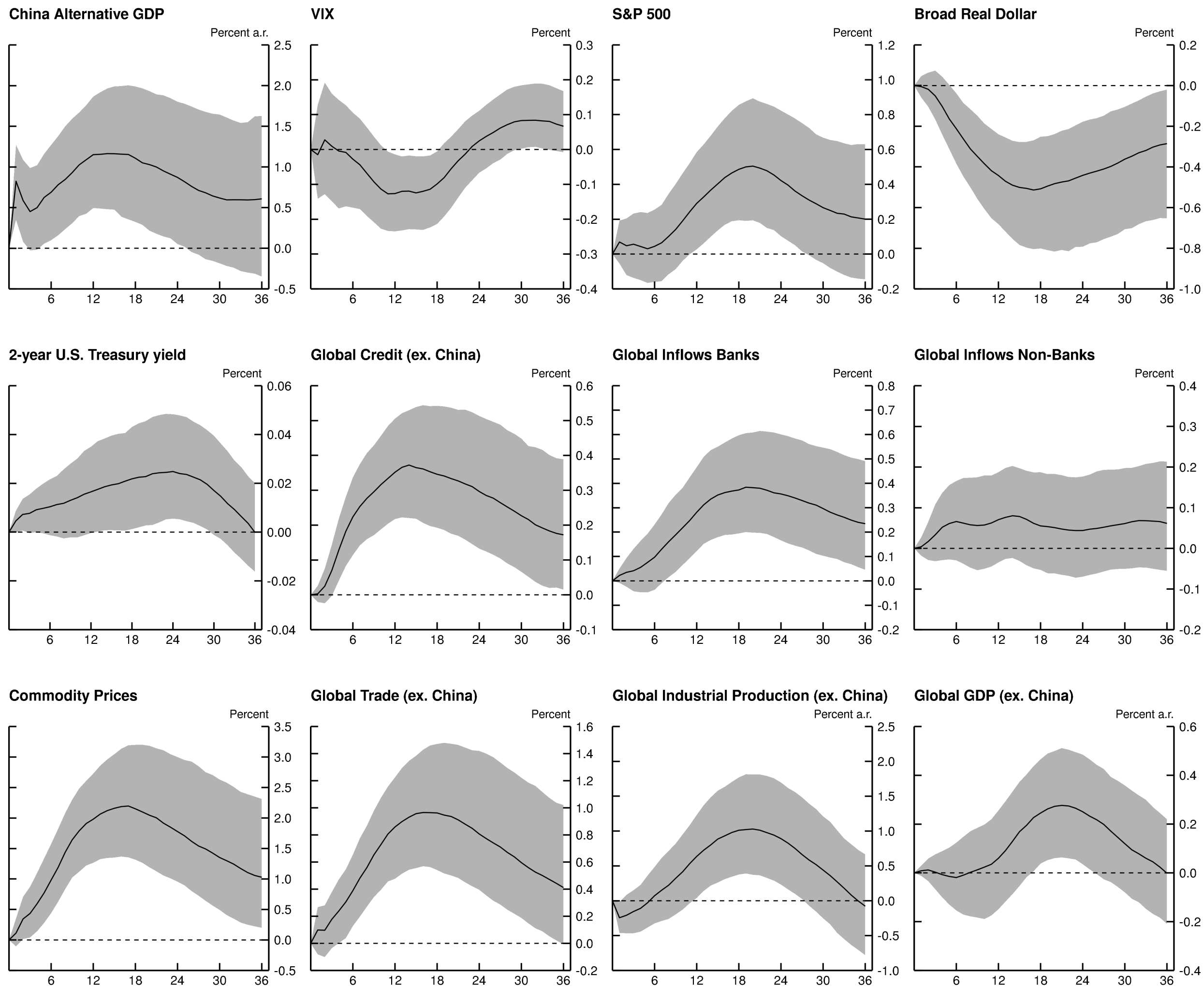



Figure 5: Impulse Responses to a Chinese Credit Impulse Shock

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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.

is that a credit impulse shock in China takes time to affect its economy and subsequently global activity. As a result, it is only as the shock is reverberating throughout the global economy that asset prices react. Second, given that Chinese GDP and certain key economic indicators appear to be overly smooth, it is difficult to extract information about underlying economic activity in China. Moreover, from official GDP data it would appear that Chinese credit stimulus policies have little effect on economic activity. As such, it is difficult to attribute changes in global activity to economic developments in China. Therefore, it is only when global real economic activity improves, that risk sentiment improves as well. This narrative is very much in line with recent episodes of deleveraging policies in China. For example, Chinese authorities started to cool the economy in 2016 by slowing credit growth as highlighted in panel B in figure 3. Our alternative GDP measure suggests that it took about 6 months for the Chinese economy to start slowing. However, global financial markets became more attuned to the global economic slowdown during mid-2018 when companies like Apple and Caterpillar downgraded their sales outlook citing weak Chinese demand and plummeting auto sales in China throughout mid-2018 and 2019 hurt European car companies. Moreover, the smoothness in GDP hid any signs of a significant slowdown in China, which made it difficult to attribute the global slowdown to a credit slowdown in China.[26]

All told, we provide evidence that, over the past decade, changes in Chinese credit conditions have had sizable spillovers to the global financial system through their effects on global risk sentiment. We argue that China constitutes an important driver of the global business cycle through international trade effects resulting from higher Chinese demand. As such, stronger Chinese demand raises global growth prospects, inducing a decline in aggregate risk aversion, proxied by the VIX, and an expansion in global asset prices and in global credit. The delayed effects on financial and economic variables outside of China also indicate 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 would boost Chinese activity.

### 5.3 Importance of China's Alternative GDP

To analyze the importance of including our alternative GDP, we re-estimate our benchmark VAR but use China's official real GDP instead of our alternative GDP measure (model 3 in table 1).[27]

Figure 6 shows that a policy-induced credit impulse shock of 1% of China's GDP does not have a significant impact on Chinese official GDP, which seems puzzling. What is even more puzzling is that spillovers from China's credit policies to the global economy are similar to those in our benchmark model. Indeed, we find that an expansionary credit shock in China leads to a decline in aggregate risk aversion and an expansion in global asset prices and credit. Similarly, we find a positive and significant effect on global business activity as commodity prices and global trade outside of China increases, leading to an expansion of global industrial production and GDP.

[26] In fact, the slowdown in global growth throughout mid-2018 and 2019 was largely attributed to a more broad-based global slowdown in the automobile sector and the downturn in the tech cycle in Asia (IMF, 2019). That said, given China's importance in global auto and high-tech goods consumption, weaker Chinese consumption resulting from China's deleveraging policies likely contributed to these cyclical downturns.

[27] Given that China's official real GDP is released at the quarterly frequency, we transform China's official real GDP to a monthly level using a piecewise cubic interpolation of the quarterly series. As part of an additional robustness exercise in appendix C, we use China's official monthly industrial production instead of official real GDP.

We interpret the results from this exercise as highlighting the importance of using our alternative GDP measure that better captures China's business cycle movements. Without it, China's credit policies appear to not significantly affect China's economy. As a result, it is difficult to attribute any global cycle movements to economic developments in China.

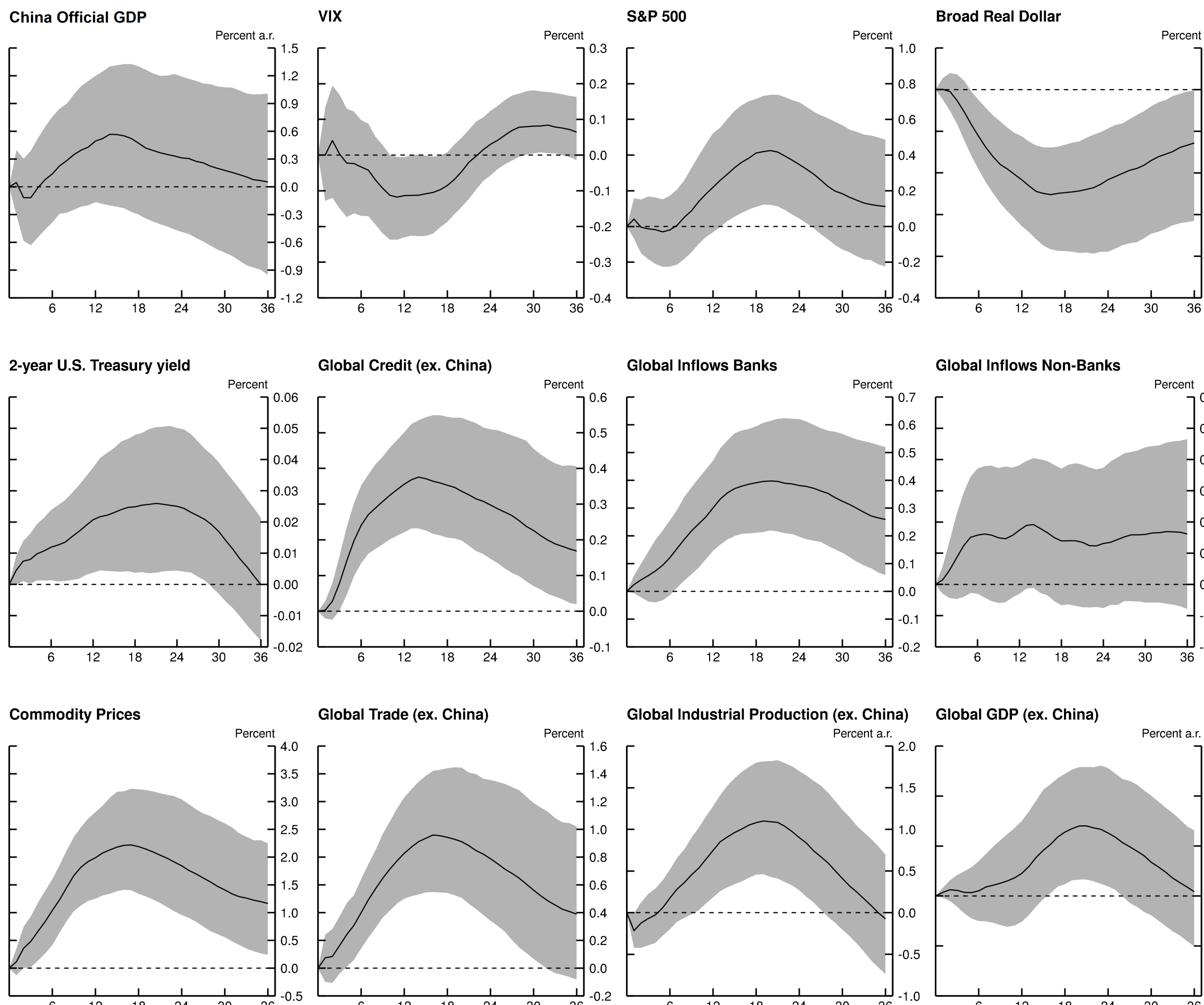



Figure 6: Impulse Responses to a Chinese Credit Impulse Shock with Official GDP

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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.

## 5.4 Importance of China's Credit Impulse

Next, we assess the importance of identifying Chinese demand shocks using our constructed credit impulse for China. As described earlier, previous research has largely focused on estimating the impact of China's activity on global activity by identifying shocks directly to Chinese GDP. However, using shocks to GDP can confound supply and demand shocks, especially given that China is a major exporter. Therefore, we analyze the importance of using the credit impulse to identify Chinese demand shocks by estimating an additional VAR that includes the same endogenous variables as in our benchmark, but identifies shocks to China's official real GDP (model 4 in table 1).

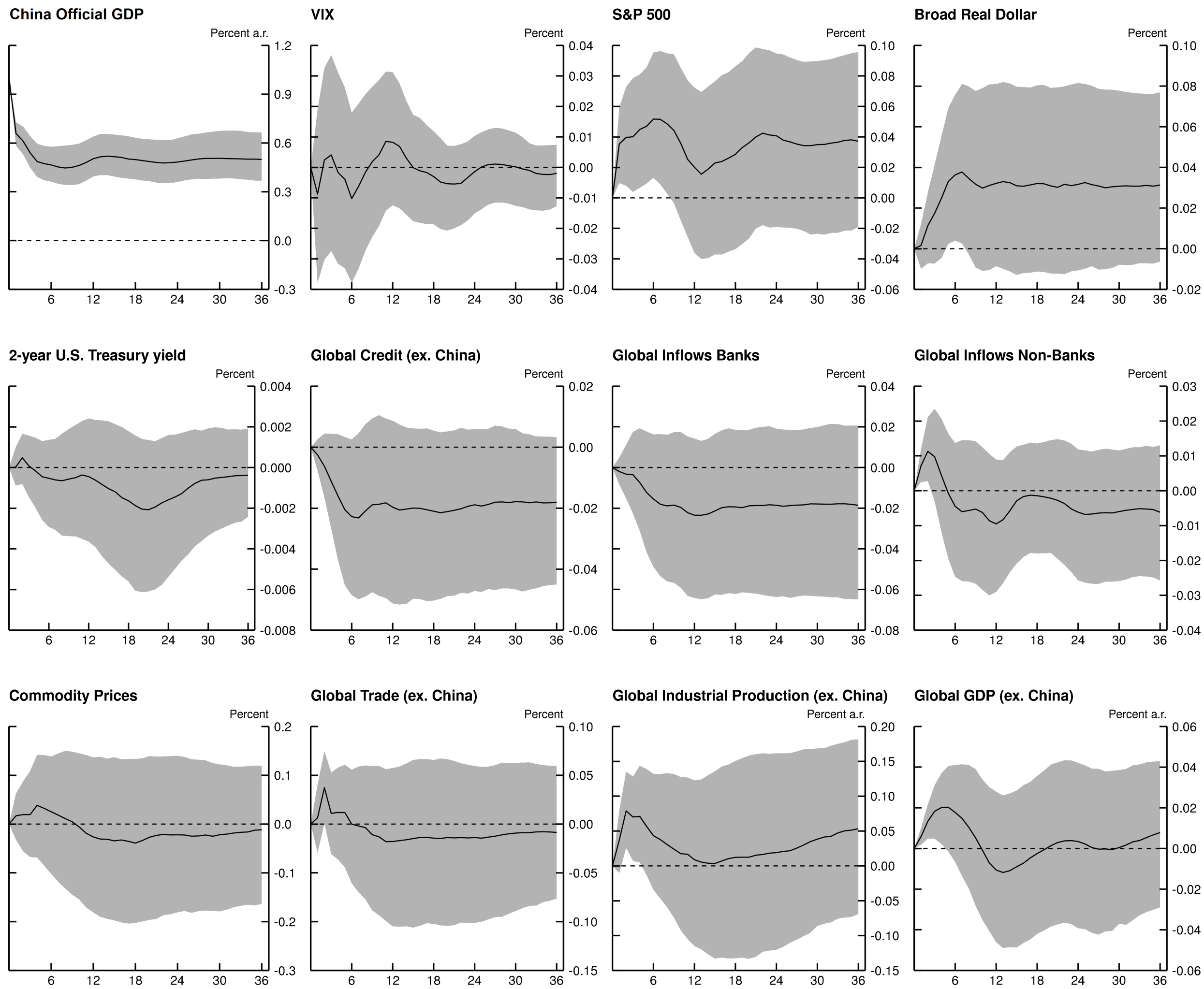



Figure 7: Impulse Responses to a 1% Shock to China's Official Real GDP

Note: The black lines are the estimated impulse responses to a 1% shock to China's real official GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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.

Figure 7 presents the impulse response functions from a 1% shock to China's official real GDP. In terms of spillovers effects, we find no significant impact on global credit outside of China nor on global bank inflows. This is in sharp contrast to our baseline VAR model results. Even though we find a positive effect on global asset prices (S&P 500), we do not find evidence for a decrease in aggregate risk aversion as there is no significant effect on the VIX. Also, the broad dollar appreciates, which is more consistent with an increase in aggregate risk aversion, although its effect is very small and barely significant over the entire horizon. We find positive and significant effects on global industrial production and global GDP excluding China, but they are quantitatively small. Moreover, the transmission channels appear to be masked in that we do not find a significant impact on global trade outside of China, nor do we find an impact on commodity prices resulting from higher Chinese demand. Again, these results are in sharp contrast to our benchmark VAR presented in figure 5. Altogether, using shocks to Chinese GDP would suggest that the Chinese economy has no spillovers to the global financial cycle, in part driven by the seemingly muted spillovers to the global business cycle.

To summarize, the previous results highlight two important methodological contributions in studying the spillovers effects from China to the rest of the world. We show that (1) using China's credit impulse to isolate Chinese demand shocks, and (2) using an alternative GDP measure for China's economy are both key to discern and quantify the contribution of China's economy to global financial and business conditions. 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 no contribution to the global financial cycle.

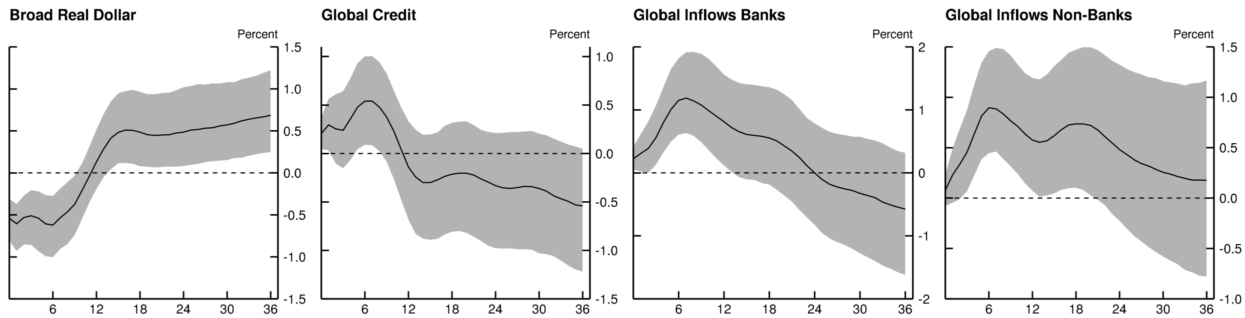
# 6 China's Role in the Global Economy

## 6.1 Importance of the US and China for the Global Financial Cycle

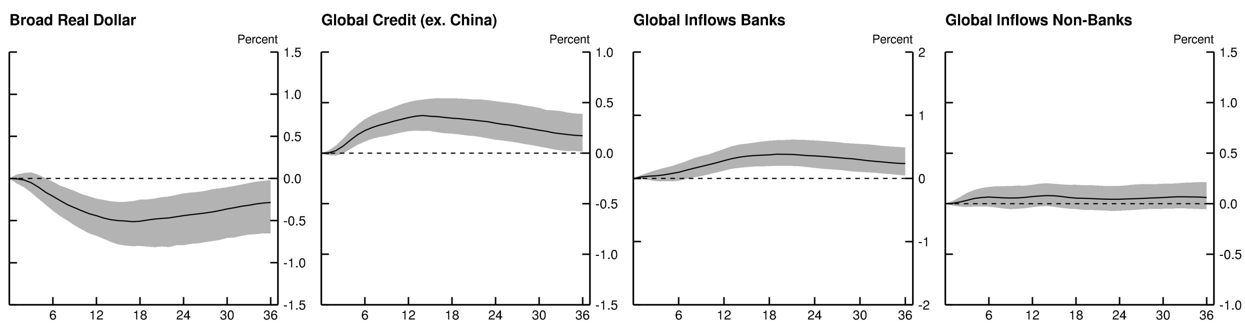
The role of the United States as an important driver of the the global financial cycle has been widely documented. Given that our results suggest China also constitutes an important driver, we compare its role to that of the United States.

A direct comparison between the United States and China is extremely difficult given China's unique institutional setup, which blurs the lines between fiscal, monetary, and regulatory policies. That said, we try to shed some light on this issue by comparing the quantitative effects from our benchmark model to those from an expansionary U.S. monetary policy shock. Specifically, panel A in figure 8 plots the economic responses for selected variables from a monetary policy shock calibrated to a 25 basis points decrease in the federal funds rate using the methodology from Miranda-Agrippino and Rey (2020). Panel B in figure 8 shows the economic responses to a credit impulse shock of 1% of China's GDP from our benchmark VAR.

There are two main takeaways from this comparison. First, we find qualitative similar effects from U.S. monetary policy easing and credit stimulus policies in China. The broad dollar depreciates and we find positive and significant spillovers to the global financial cycle as global domestic credit rises notably. Second, the effects of a policy-induced Chinese credit expansion of 1% of GDP on global credit are about half the size of a 25 basis points reduction in the federal funds rate.




Panel A: Economic Responses to an Expansionary U.S. Monetary Policy Shock of 25 bps




Panel B: Economic Responses to a Chinese Credit Impulse Shock of 1% of GDP

Figure 8: Country Comparison of Contribution to the Global Financial Cycle

Note: Panels A and B compare the effects of a 25 basis points decrease in the federal funds rate using the the methodology from Miranda-Agrippino and Rey (2020) to those from a Chinese credit impulse shock of 1% of GDP, respectively. The black lines correspond to the posterior median estimates. The VAR in panel A is estimated from January 2011 to April 2019. The VAR in panel B is estimated from January 2011 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.

Altogether, if we compare the results from our benchmark model to the literature that focuses on the role of U.S. monetary policy as an important driver of the global financial cycle, it appears that the channels of financial spillovers from China's credit policies are different from those stemming from the United States. As documented in Miranda-Agrippino and Rey (2020) financial spillovers from U.S. monetary policy transmit through mainly through global financial actors given that the

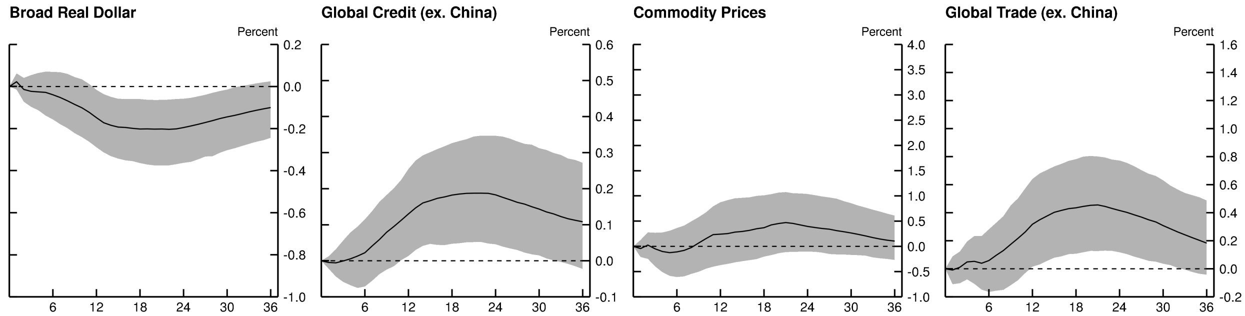
United States is highly interconnected in the global financial system. Expansionary U.S. monetary policy shocks are followed by a significant increase in leveraging of global financial intermediaries, a decline in aggregate risk aversion, an expansion in global asset prices and global credit, a narrowing of corporate bond spreads, and a rise in gross capital flows. In contrast to the United States, China does not have a big presence in global financial markets. Yet, our results suggest that spillovers from China reverberate through the global financial system predominantly through sentiment effects. Expansionary credit policies in China lead to an increase in Chinese consumption, which raises global growth. Higher global growth prospects lead to an increase in global risk sentiment and an expansion in global asset prices and global credit.

## 6.2 Importance of China's Spillovers over Past Decades

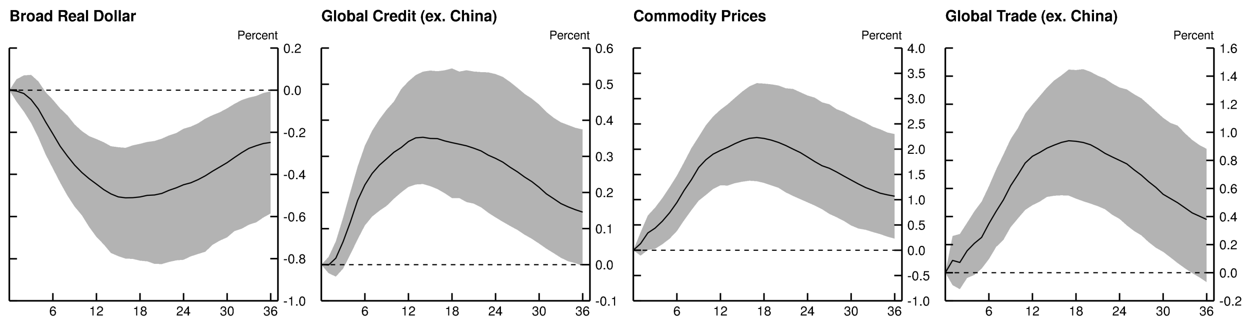
China's footprint in the global economy has expanded tremendously over the past decades. In 2000, China's economy represented about 4% of global GDP. Twenty years later, that share has grown fourfold, making it the second largest economy in the world behind the United States. Moreover, China's contribution to global growth has surged from about 10% in the 2000s to 34% in the 2010s. In this section, we document how spillovers from China to the rest of the world have changed with its increasing contribution to global GDP and growth.

Panels A and B in figure 9 show the economic responses for our benchmark VAR model but estimated for different time spans, that is, from 2000 to 2019 and from 2011 to 2019, respectively. For this analysis we use our alternative GDP measure estimated from 1999 to 2019 in order to have a comparable growth series across different time horizons to use in our VAR estimation.[28] The comparison across panels A and B highlights that spillovers from policy-induced credit changes in China have become more sizeable over the past decade. Indeed, the depreciation of the broad real dollar is nearly twice the size since 2011 compared to the average response from 2000. Similarly, the transmission to global financial and economic activity has grown notably with stronger effects on global credit, commodity prices, and global trade outside of China. All told, these results show that China's growing economic footprint in the global economy has been accompanied with larger spillovers to global financial conditions and global business activity.

[28] Figure 9 focuses on a subset of variables. For the full set of impulse response functions in panels A and B, see figures C.3 (2000 to 2019) and 5 (2011-2019) in appendix C.




Panel A: 2000-2019




Panel B: 2011-2019

Figure 9: China's Changing Contribution to the Global Financial and Business Cycle

Note: Panels A and B compare the effects for the benchmark VAR model of a Chinese credit impulse shock of 1% of GDP estimated for different time spans, namely, from January 2000 to December 2019 and from January 2011 to December 2019, respectively. 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.

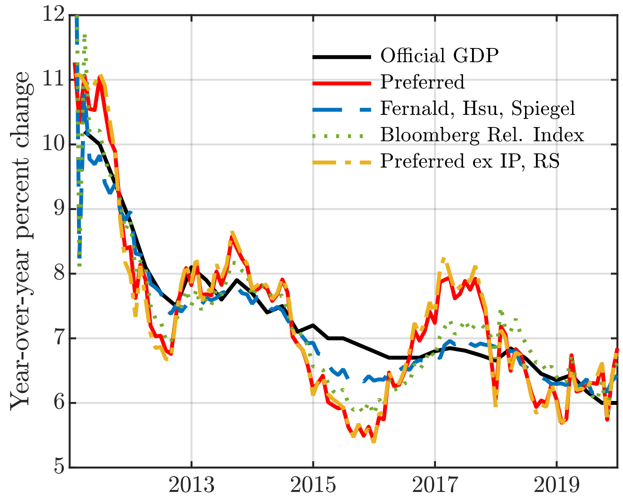
# 7 Robustness

## 7.1 China's Alternative Growth Specification

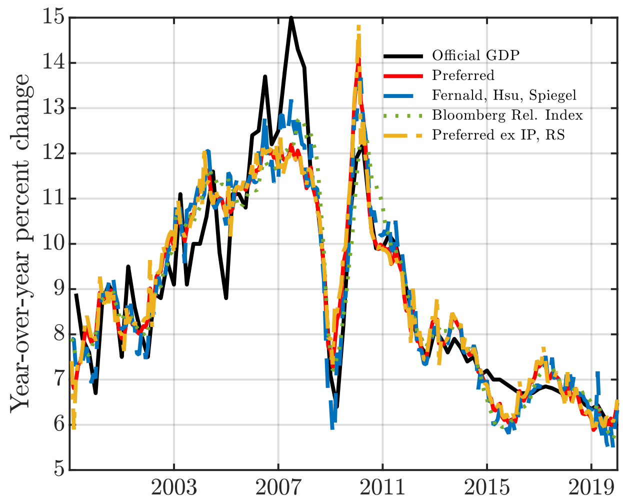
We test the sensitivity of our alternative growth series for China and, using the same methodology, estimate three additional alternative models to proxy for underlying Chinese growth. The first uses the series from Fernald et al. (2021). The second uses the series that financial market participants place the highest weight on according to the Bloomberg Relevance Index.[29] The third uses the same series as the benchmark model but excludes industrial production and retail sales given data concerns about excessive smoothness in both series.[30] We present results for the different models estimated from 2011 and from 1999.

[29] The selection of variables is similar to the approach employed by Cascaldi-Garcia et al. (2020) for now-casting euro area GDP.

[30] See appendix B for the exact alternative model specifications.




Panel A: 2011-2019




Panel B: 1999-2019

Figure 10: Comparison of Alternative Growth Model Specifications

Note: The black line plots China's official real GDP in 4-quarter changes together with four different alternative Chinese GDP series in 12-month growth rates: (1) our preferred model (red line); (2) Fernald, Hsu, Spiegel model (blue line); (3) Bloomberg Relevance Index model (green line), and (4) our preferred model excluding industrial production (IP) and retail sales (RS) (yellow line). Panel A compares each model estimated from 2011-2019 and panel B from 1999-2019.

Panel A in figure 10 presents the model comparisons for the different DFMs estimated from 2011 to 2019. It highlights that all models point to a more pronounced Chinese business cycle compared to official data. That said, the fluctuation in GDP growth for the Fernald, Hsu, Spiegel model and the Bloomberg Relevance Index model is more muted compared to our preferred model. While they both show a more pronounced downturn in 2015 relative to official growth, it has been more or less in line with official growth since 2017. Therefore, it appears to not capture the strong economic upswing after China's 2016 credit stimulus period and the subsequent sharper-than-reported slowdown from the end of 2017 onward, captured by our preferred model. This divergence appears to be driven by the difference in the set of underlying series. The majority of the data series in the other estimated models are tilted toward the manufacturing sector, whereas our preferred model also includes numerous services series. Given that the 2015 downturn was largely concentrated in the manufacturing sector, the models capture similar movements around that period. 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 appears to better capture the more recent fluctuations in Chinese GDP.

Panel B in figure 10 presents the same model comparisons, but estimated from 1999. It illustrates that all alternative models show a very similar pattern. All alternative series capture the large drop in economic growth and subsequent recovery during the GFC episode. Interestingly, the alternative series also find a similar pattern in recent years. They all show a stronger downturn in the 2015 economic slowdown and a stronger upturn in the subsequent stimulus period. All told, these results highlight that the different models, estimated from 1999 onward, show similar growth series for China, with more marked business cycles compared to official GDP.[31] [32]

### 7.2 VAR Specification

We perform a robustness exercise in which we use a different measure for Chinese activity that does not rely on our alternative growth estimation. Fernald et al. (2021) argue that Chinese imports provide a good proxy for Chinese domestic demand, which is correlated with underlying Chinese activity. The authors construct a Chinese import series using total foreign reported exports to China and Hong Kong, taking into consideration the concern of potential under-reporting in official Chinese import data. Following the same methodology, we construct a Chinese import series that we use instead of our alternative measure for Chinese official real GDP.[33]

As illustrated in figure 11, we find that a credit impulse shock of 1% of China's GDP significantly

[31] Figures B.3, B.4, B.5, and B.6 in appendix B plot the individual weights the DFM places on each of the underlying series. Each model assigns a relatively large weight to Chinese exports, which likely also explains the similarity across series. However, as we documented earlier, China's economy has shifted from an export driven and investment-led economy to a more consumption-based economy in recent years. Indeed, China's dependence on exports has declined notably after the GFC as illustrated in figure A.2 in appendix A, which plots Chinese gross and value added exports as a share of GDP.

[32] One caveat is that all models appear to not fully capture the variation in real GDP growth in the period before the GFC.

[33] The VAR specification is described in table C.1 in appendix C (model 7). We perform additional robustness exercises.

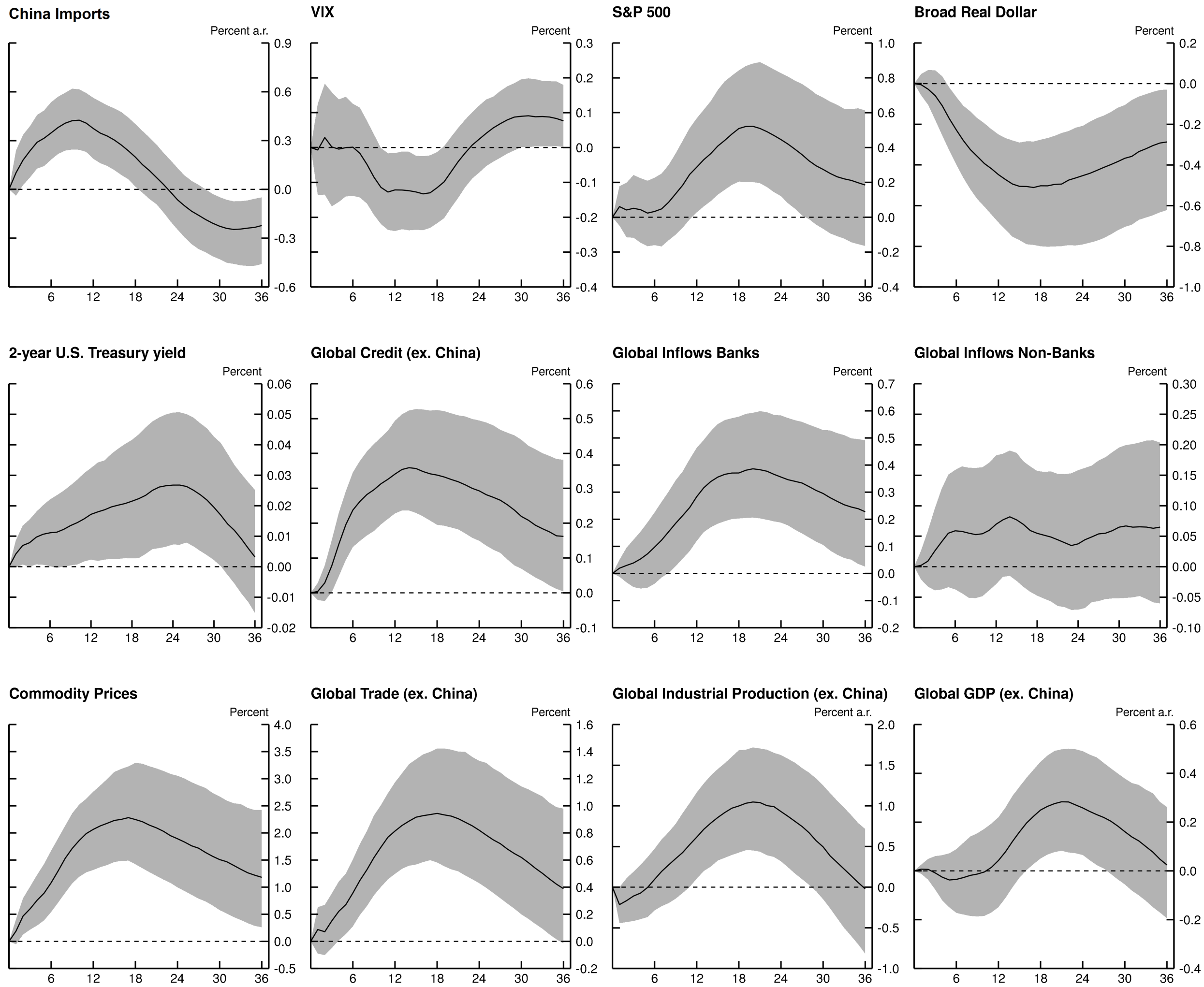



Figure 11: Impulse Responses from a Chinese Credit Impulse Shock with Chinese Imports

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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.

increases Chinese imports, with the strongest effects after 10 months, and positive effects for about 18 months. Moreover, the economic responses outside of China are qualitatively and quantitatively very similar to those in our benchmark VAR model (figure 5). Indeed, the results show significant and positive spillovers to global financial and economic conditions. Global credit outside of China increases notably as global risk aversion diminishes, evidenced by a decline in the VIX, higher asset prices, and a depreciation of the broad dollar. Similarly, we find significant and economically meaningful spillovers to economic activity outside of China. Global industrial production and GDP excluding China rise notably amid stronger Chinese demand, which in turn pushes up commodity prices and global trade outside of China. The results in figure 11 also provide further evidence of the transmission channel from China to the rest of the world. Indeed, the impulse response functions illustrate that China's credit policies constitute an important driver of Chinese demand (imports), which leads the upturn in commodity prices and global trade, and consequently global industrial production outside of China.

## 8 Conclusion

China's economy has grown rapidly over the past decades and has transformed the global landscape with it. Its economy is the second largest in the world and accounts for more than a third of global growth. With China's increasing footprint in the global economy, we study its role as a driver of fluctuations in global financial conditions. We do so by addressing two significant hurdles when studying China's role in the global economy. The first hurdle is the challenge of isolating Chinese demand shocks. To that end, we take advantage of the fact that the Chinese authorities exert a significant degree of control over the supply of credit to the economy. We construct a measure of China's credit impulse, which is an aggregate of different types of credit influenced by the Chinese authorities to identify policy-induced demand shocks. The second hurdle is related to data concerns regarding official GDP. Chinese GDP appears implausibly smooth, a problem that appears to have become more acute during the 2010s. We construct an alternative growth series for China that better captures the fluctuations of underlying Chinese economic activity. After addressing these data challenges, we estimate a Bayesian Vector Autoregressive Model (VAR) to quantify the impact of policy-induced changes in China's credit impulse on Chinese economic activity, proxied by our alternative GDP measure, and the spillovers to global financial conditions. Our results show that since the GFC, China constitutes an important driver of the global financial cycle. To the best of our knowledge, this is the first paper that provides direct evidence for this relationship. We find that China's expansionary credit policies notably increase global credit outside of China driven by an increase in aggregate risk sentiment. We argue that, unlike the United States, which is a financial center of the world, spillovers from China to global financial markets reflect its importance as a driver of global business activity. Specifically, we find that expansionary credit policies in China lead to notable increases in commodity prices, global production, and GDP outside of China driven by higher Chinese demand. As such, stronger Chinese consumption raises global growth prospects, inducing a decline in aggregate risk aversion, proxied by the VIX, and an expansion in global asset prices and credit.

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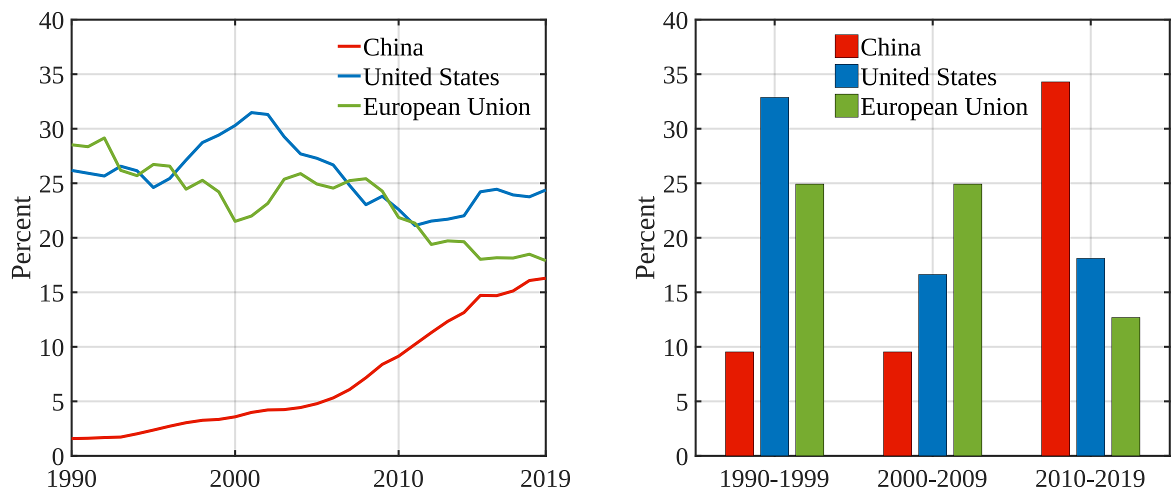
# Appendix A: Background on China's Economy

Decades of sustained rapid growth have transformed China's economy and, with it, the global economic landscape. Panel A in figure A.1 plots Chinese GDP, valued at market exchange rates, as a share of global GDP. In 1990, China's economy represented only 2% of global GDP despite being home to a quarter of the world's population. Thirty years later, that share has grown eight-fold to 16% of global GDP, making it the second largest economy in the world behind the United States, which represents about 24% of global GDP. Moreover, as panel B in figure A.1 shows, China's contribution to global growth has expanded notably from less than 10% in the 1990s and 2000s to 34% in the 2010s, which is higher than the growth contributions of the U.S. and the EU combined.




Panel A: Share of global GDP (%)　　Panel B: Share of global growth (%)

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

Note: Panel A plots nominal GDP as a share of global GDP for China, the United States, and the European Union. Panel B plots the contribution to global nominal growth for the past three decades. The European Union includes Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, and Sweden.

As has been widely documented, China's rise has gone hand in hand with its emergence as an export powerhouse, in part supported by joining the WTO in 2001. Indeed, export growth has been a key driver of China's growth in the decade before the Great Financial Crisis (GFC), as highlighted in figure A.2. China's exports as a share of its GDP surged from about 20% in the 1990s to over 30% during the 2000s. Similarly, value added in Chinese exports as a share of GDP also surged from about 17% in the 1990s to about 25% during the 2000s.

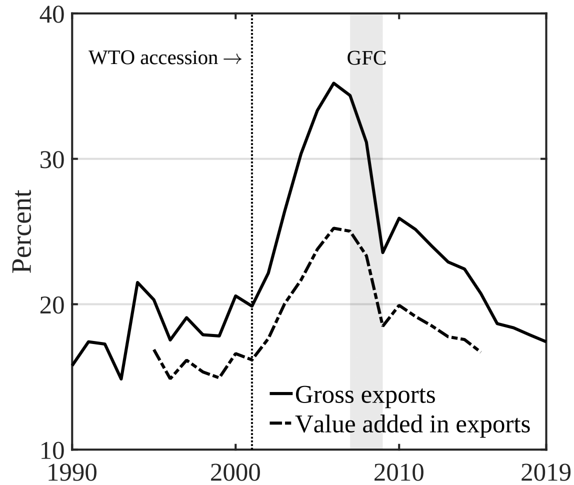



FIGURE A.2: EXPORT SHARE OF GDP (%)

Note: The solid line represents Chinese exports as a share of its nominal GDP. The dashed-dotted line represents the value added in Chinese exports as a share of its nominal GDP.

That said, figure A.2 also highlights that the export contribution to China's GDP has declined notably in the 2010s. The collapse of external demand during the GFC in 2008 and the anemic recovery in advanced economies that followed, meant that China could no longer rely on exports to sustain rapid growth.[34] As a result, the Chinese government responded with massive credit stimulus oriented mainly towards investment. Indeed, as illustrated by figure A.3, domestic credit expanded by nearly 25% of GDP.

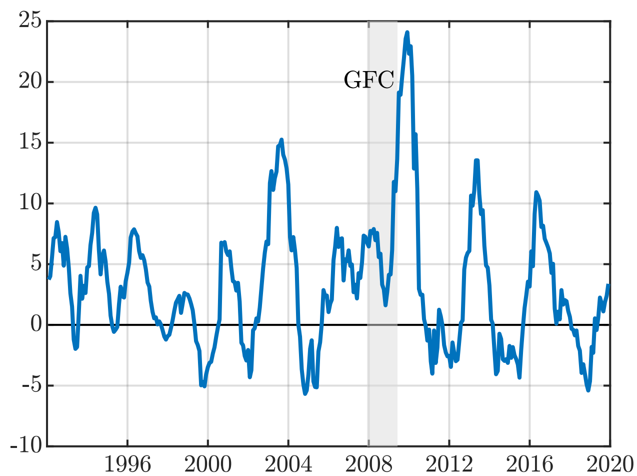
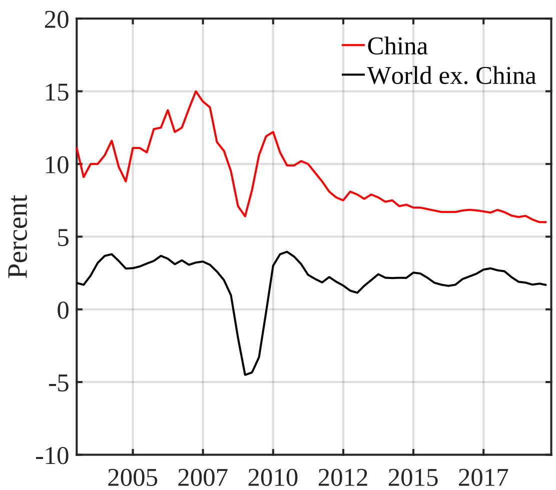



FIGURE A.3: CHINESE CREDIT IMPULSE (%)

Note: China's credit impulse is calculated as the change in the flow of new credit in the past 12 months relative to those the year prior as a percent of China's nominal GDP.

[34]The net export contribution of goods and services to real GDP growth has also fallen since the GFC.

Since the GFC, Chinese growth has been increasingly supported by domestic demand. And given China's outsized contribution to global growth, Chinese credit policies and their impact on domestic demand have been increasingly cited as an important driver of the global business cycle. For example, China's massive credit stimulus after the GFC was cited as a prominent driver of the rapid recovery and driving up commodity prices. Conversely, China's subsequent policies to rein in credit growth in order to reduce financial risks in the Chinese economy in 2014-2015 and more recently at the end of 2016 featured prominently in many accounts as a key driver of slower growth and falling commodity prices.




Panel A: Real GDP Growth


Panel B: Industrial Production Growth

Figure A.4: China's Economy and the Global Business Cycle

Note: Panels A and B 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.

Despite the fact that China figures prominently in many accounts of the drivers of fluctuations in global growth, it has become increasingly difficult to attribute global business cycle movements to economic developments in China. To illustrate this issue, figure A.4 compares China's business cycle to the global business cycle. Panel A plots 4-quarter GDP growth for China and the world excluding China. Panel B plots 12-month industrial production growth for China and the world excluding China. Both panels show that China's economic activity appears uncorrelated with the global cycle, especially in the later years of the 2010s. This seems at odds with China's prominence as a global consumer and therefore raises concerns about official GDP data. Specifically, there is a longstanding concern that China's GDP is overly smoothed Nakamura et al. (2016), a problem that, according to some, has become acute during the 2010's (Clark et al., 2020; Groen and Nattinger, 2020; Fernald et al., 2021). Therefore, in this paper, we build on previous research and construct an alternative measure of Chinese real GDP that relies on a large set of indicators that are informative about the Chinese business cycle.

# Appendix B: Data Appendix

## B.1 Global GDP Volatility

The sample in panel B of figure 2 includes the following 108 countries: Albania, Argentina, Australia, Austria, Azerbaijan, Bahrain, Belarus, Belgium, Belize, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei, Bulgaria, Cameroon, Canada, Chile, China, Colombia, Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Georgia, Germany, Ghana, Greece, Guatemala, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lesotho, Lithuania, Luxembourg, Macao, Malaysia, Malta, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Nicaragua, Nigeria, North Macedonia, Norway, Palestinian Territories, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Saudi Arabia, Senegal, Serbia, Seychelles, Singapore, Slovak Republic, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, United Kingdom, United States, Uganda, Ukraine, Uruguay, Venezuela, Vietnam, and Zambia.

## B.2 China's Credit Impulse

Figure B.1 plots two credit impulse series. The first series is computed using China's raw Total Social Financing (TSF) series, which is a monthly data series for domestic credit that the People's Bank of China (PBOC) release. The second series is our preferred credit impulse, which augments the TFS series with local government bonds and adjusts for double counting of special local government bonds. Both series line up well up until around 2015. In the aftermath of the 2015 economic slowdown, Chinese authorities responded with substantial credit stimulus, which was in large part driven by local government bond issuance. Therefore, accounting for local government bond issuance is crucial in determining the correct timing of the stimulus period as, according to the credit impulse based on TSF data, the height of the stimulus period is identified incorrectly at the end of 2017.

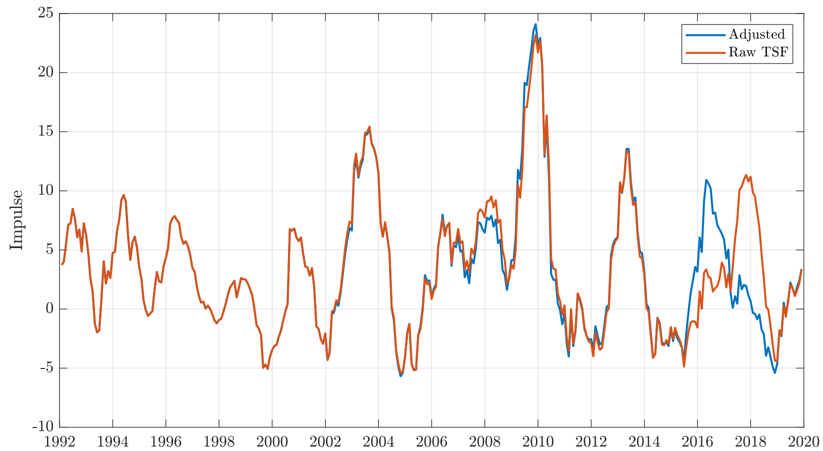



Figure B.1: Preferred credit impulse versus credit impulse based on raw TSF data (%)

Note: Figure B.1 plots China's credit impulse computed using raw total social financing (TSF) data and our preferred measure for China's credit impulse, which adjusts the TSF measure for local and special local government bonds.

## B.3 Alternative GDP Level

Figure B.2 presents the imputed monthly GDP growth rates, $y_t$, estimated from the state-space model 9 and the adjusted GDP growth rates, $\tilde{y}_t^*$, as computed by equation 12, which are used to estimate our Chinese alternative GDP level series.

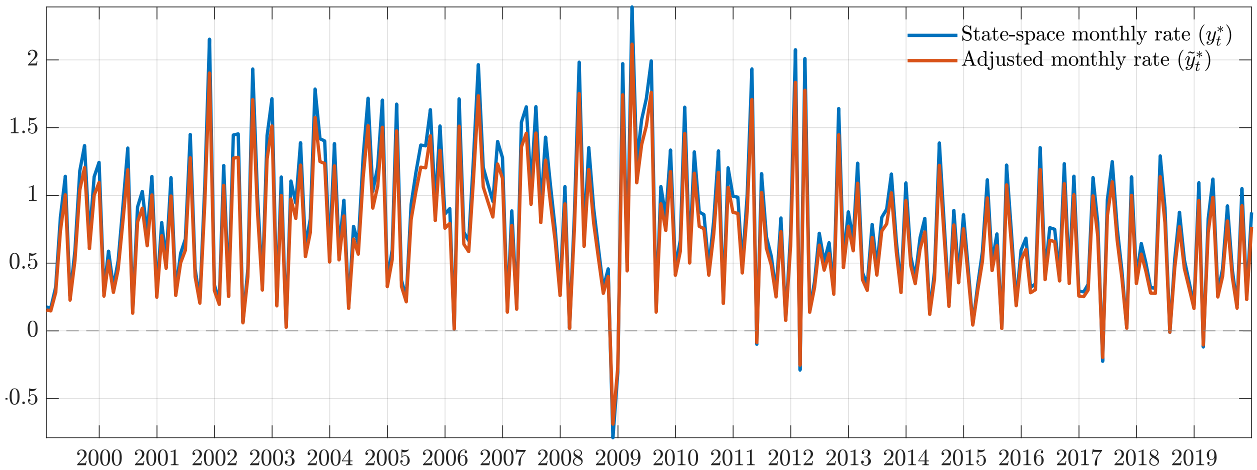



FIGURE B.2: MONTHLY GDP GROWTH RATES

Note: Figure B.2 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.

## B.4 Model Specifications

Table B.1: Model Specifications

| Indicators | Source | Period | Preferred | Fernald, Hsu, Spiegel | Bloomberg Rel. Index | Preferred ex. IP, RS |
|---|---|---|---|---|---|---|
| Industrial production | CEIC | m | x | x | x | |
| Retail sales | CEIC | m | x | x | x | |
| Fixed asset investment | CEIC | m | | x | x | |
| Fixed asset investment (manuf.) | CEIC | m | x | | | x |
| Fixed asset investment (serv.) | CEIC | m | x | | | x |
| Real estate investment | CEIC | m | x | | x | x |
| Consumer expectation index | CEIC | m | x | x | | x |
| Electricity consumption | CEIC | m | x | x | | x |
| Electricity production | CEIC | m | x | | | x |
| Chinese exports | CEIC | m | x | x | x | x |
| Chinese imports | CEIC | m | | | x | |
| Chinese imports (foreign reported) | Haver | m | x | | | x |
| Floor space started | CEIC | m | x | x | | x |
| Floor space sold | CEIC | m | x | | | x |
| Railway freight | CEIC | m | x | x | | x |
| Cement production | CEIC | m | x | | | x |
| Auto sales | CEIC | m | x | | | x |
| Household items production | CEIC | m | x | | | x |
| Copper import volume | CEIC | m | x | | | x |
| Microcomputer production | CEIC | m | x | | | x |
| Semiconductor production | CEIC | m | x | | | x |
| Steel production | CEIC | m | x | | | x |
| Ali Baba sales | Ali Baba | q | x | | | x |
| Lenovo sales | Lenovo | q | x | | | x |
| Tencent sales | Tencent | q | x | | | x |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Excavator sales | CEIC | m | x | | | x |
| Copper import volume | CEIC | m | x | | | x |
| Iron ore import volume | CEIC | m | x | | | x |
| Caixin PMI (comp.) | CEIC | m | | | x | |
| Caixin PMI (manuf.) | CEIC | m | x | | x | x |
| Caixin PMI (serv.) | CEIC | m | | | x | |
| Official PMI (comp.) | CEIC | m | | | x | |
| Official PMI (manuf.) | CEIC | m | | | x | |
| Official PMI (serv.) | CEIC | m | | | x | |
| Satellite Nightlights | NOAA | m | x | | | x |
| Nitrogen Dioxide (NO2) | TEMIS | m | x | | | x |
| Official GDP | CEIC | m | | | x | |
| Industrial profits | CEIC | m | x | | x | x |
| Foreign direct investment | CEIC | m | | | x | |
| New home prices | CEIC | m | | | x | |
| TOTAL | | | 30 | 8 | 16 | 28 |

## B.5 Factor Loadings

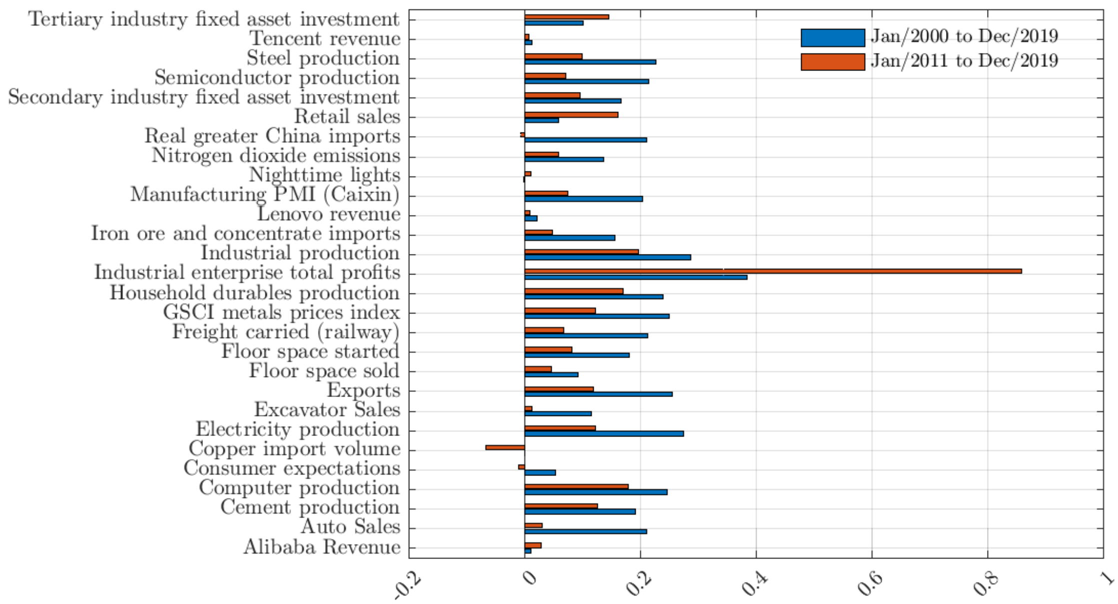



FIGURE B.3: DFM LOADINGS - PREFERRED MODEL

Note: Figure B.3 plots the factor loadings for our preferred model estimated over the samples Jan/2000 to Dec/2019 and Jan/2011 to Dec/2019.

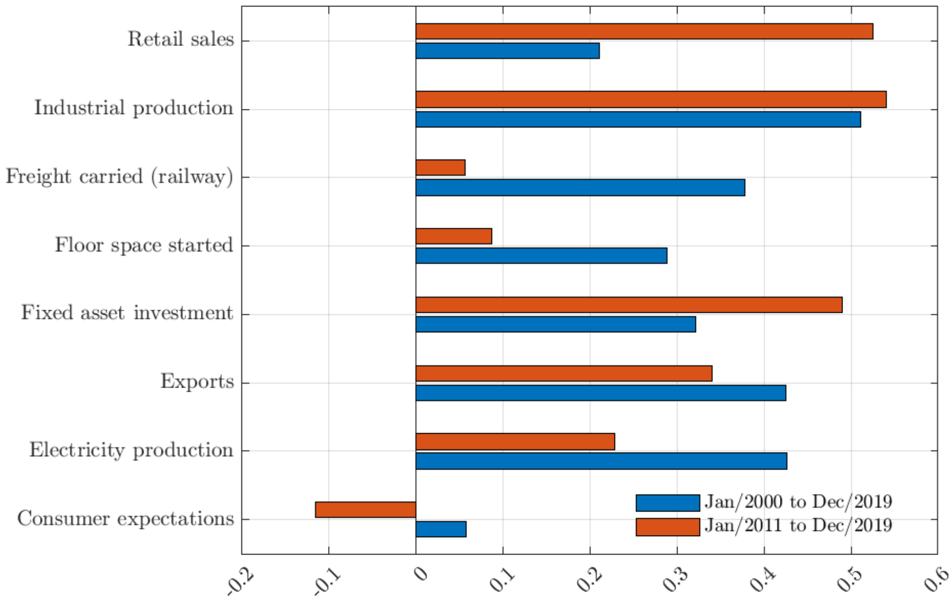



Figure B.4: DFM loadings - Fernald, Hsu, Spiegel model

Note: Figure B.4 plots the factor loadings for the Fernald, Hsu, Spiegel model estimated over the samples Jan/2000 to Dec/2019 and Jan/2011 to Dec/2019.

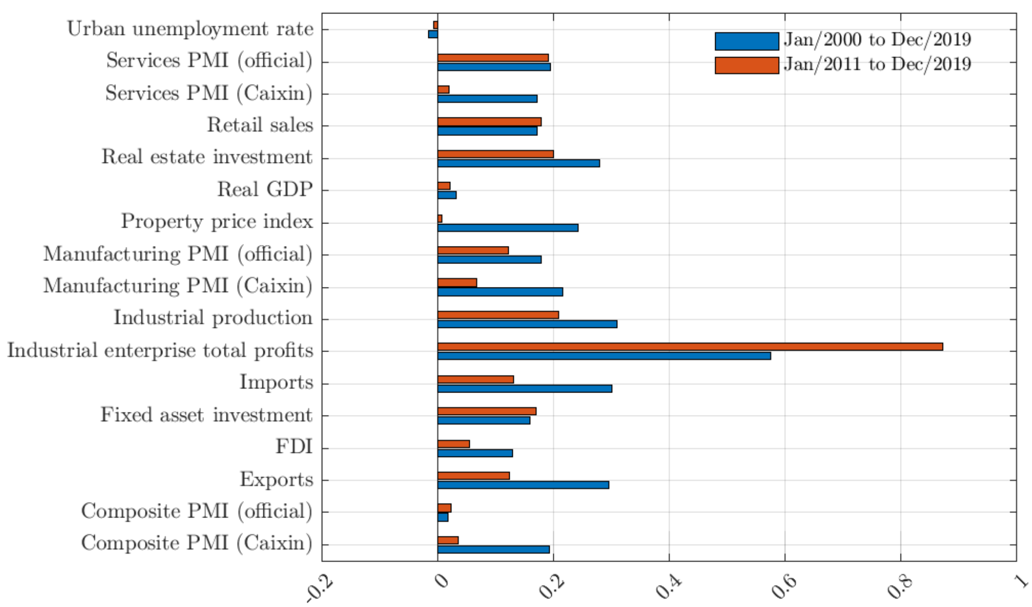



Figure B.5: DFM loadings - Bloomberg Relevance Index model

Note: Figure B.5 plots the factor loadings for the Bloomberg Relevance Index model estimated over the samples Jan/2000 to Dec/2019 and Jan/2011 to Dec/2019.

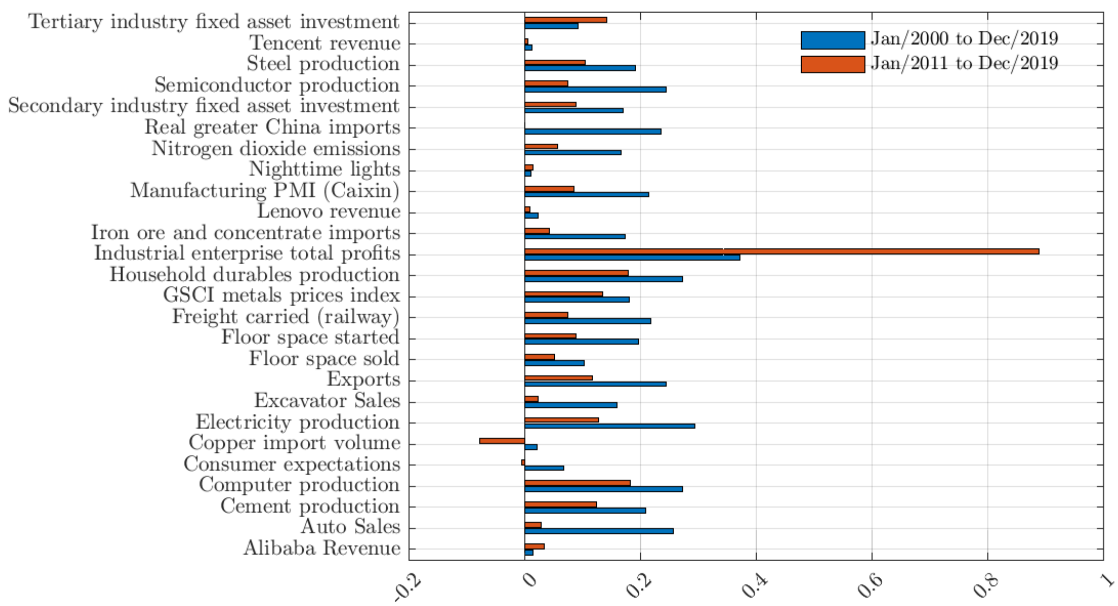



FIGURE B.6: DFM LOADINGS - PREFERRED EX IP, RS MODEL

Note: Figure B.6 plots the factor loadings for the preferred model ex industrial production and retail sales estimated over the samples Jan/2000 to Dec/2019 and Jan/2011 to Dec/2019.

## Appendix C: Additional VAR Results

Table C.1 presents additional VAR specifications we estimate.

Table C.1: Additional VAR Model Specifications

| Variable name | Source | Model | | | | |
|---|---|---|---|---|---|---|
| | | (5) | (6) | (7) | (8) | (9) |
| China's credit impulse | Own calculation | x | x | x | x | |
| Alternative Chinese real GDP† | NBS | x | x | | | |
| Global financial cycle | Miranda-Agrippino and Rey (2020) | x | | | | |
| Global economic conditions | Baumeister et al. (2022) | x | | | | |
| Chinese imports | Own calculation | | | x | | |
| Official Chinese IP | NBS | | | | x | x |
| VIX | Haver | | x | x | x | x |
| S&P 500 | Haver | | x | x | x | x |
| Broad U.S. dollar | BIS* | | x | x | x | x |
| 2-year U.S. Treasury yield | FRB | | x | x | x | x |
| Global credit flows ex. China | BIS*, Own calculation | | x | x | x | x |
| Global inflows to banks | BIS* | | x | x | x | x |
| Global inflows to non-banks | BIS* | | x | x | x | x |
| Commodity price index | Haver | | x | x | x | x |
| Global Trade ex. China | Haver, Own calculation | | x | x | x | x |
| Global IP ex. China | Haver, Own calculation | | x | x | x | x |
| Global GDP ex. China | NBS,* Own calculation | | x | x | x | x |
| Figures | 2011-2019 | C.1 | C.2 | 11 | C.5 | C.6 |
| Figures | 2000-2019 | | C.3 | | | |
| Figures | 2000-2007 | | C.4 | | | |

Note: The top panel lists the variables included in the different VAR model specifications. † The alternative Chinese real GDP growth measure is estimated from January 1999 to December 2019. 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 describes the corresponding figures for each model estimation and for different time spans.

### C.1 Narrow and Benchmark Model - GDP Estimated from 1999-2019

In this section, we re-estimate models 1 and 2 in table 1, but use our alternative Chinese GDP measure estimated from 1999-2019 (model 5 and 6 in table C.1) to analyze the robustness of our results to different alternative GDP specifications.

Figures C.1 and C.2 present the impulse response functions for our narrow, four-variable model and our benchmark model, respectively. Overall, we find that our results are robust to the different alternative GDP specification for China. We find that a policy-induced increase in China's credit impulse of 1% of GDP leads to a significant rise in our alternative growth measure of Chinese GDP with positive and significant spillovers to the global financial and business cycle as illustrated in figure C.1.

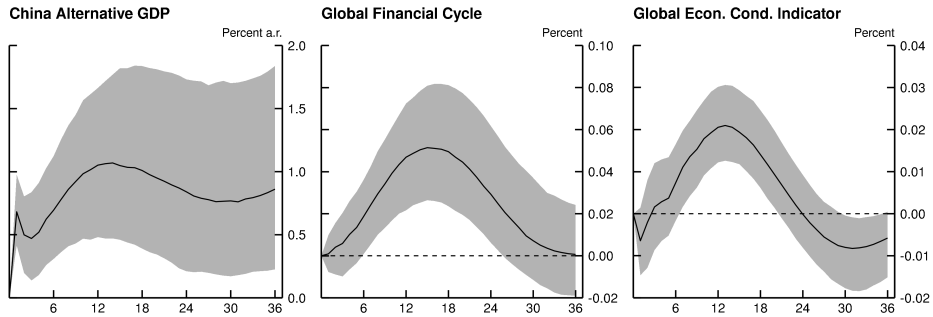



Figure C.1: Impulse Responses to a Chinese Credit Impulse Shock

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock and correspond to the posterior median estimates. The VAR is estimated from January 2011 to April 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.

We do find that the effects of China's credit policies on its own economy are a bit dampened when using our alternative GDP measure estimated from 1999. We find that a policy-induced increase in China's credit impulse of 1% of GDP boosts its own economy by 0.7% as shown in figure C.2, which is slightly lower than our benchmark effect of 1.2% in figure 5.[35] That said, we find that the spillover effects to the rest of the world are quantitatively similar. After one to two years, the credit shock is estimated to induce a 0.3% increase in global GDP outside of China and raise commodity prices and global trade excluding China by 2.2% and 1%, respectively, boosted by stronger Chinese demand. In addition, we find that the effects on the rest of the world lag the positive effects on Chinese GDP, pointing to a transmission from China's economy to the rest of the world, and not vice-versa. All told, our results are robust to the different alternative GDP specification we use.

## C.2 Importance of China's Spillovers - All VAR Results

Figures C.3 and C.4 present the full set of impulse responses for our benchmark model, estimated for different time horizons, that is, from 2000-2019 and 2000-2007, respectively.

[35] We attribute the dampened effect to the somewhat lower volatility of our alternative GDP measure estimated from 1999-2019.

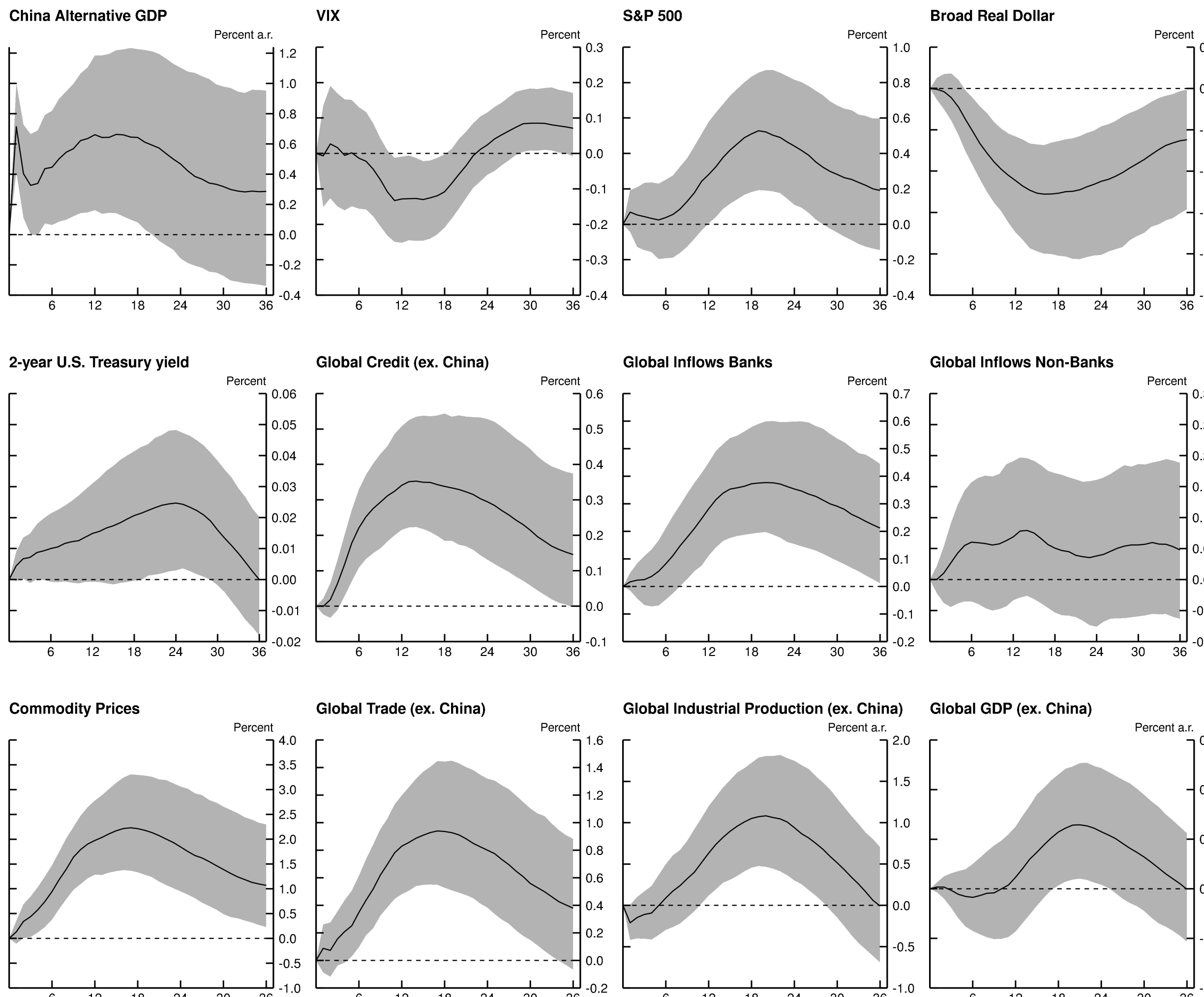



Figure C.2: Impulse Responses to a Chinese Credit Impulse Shock

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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.

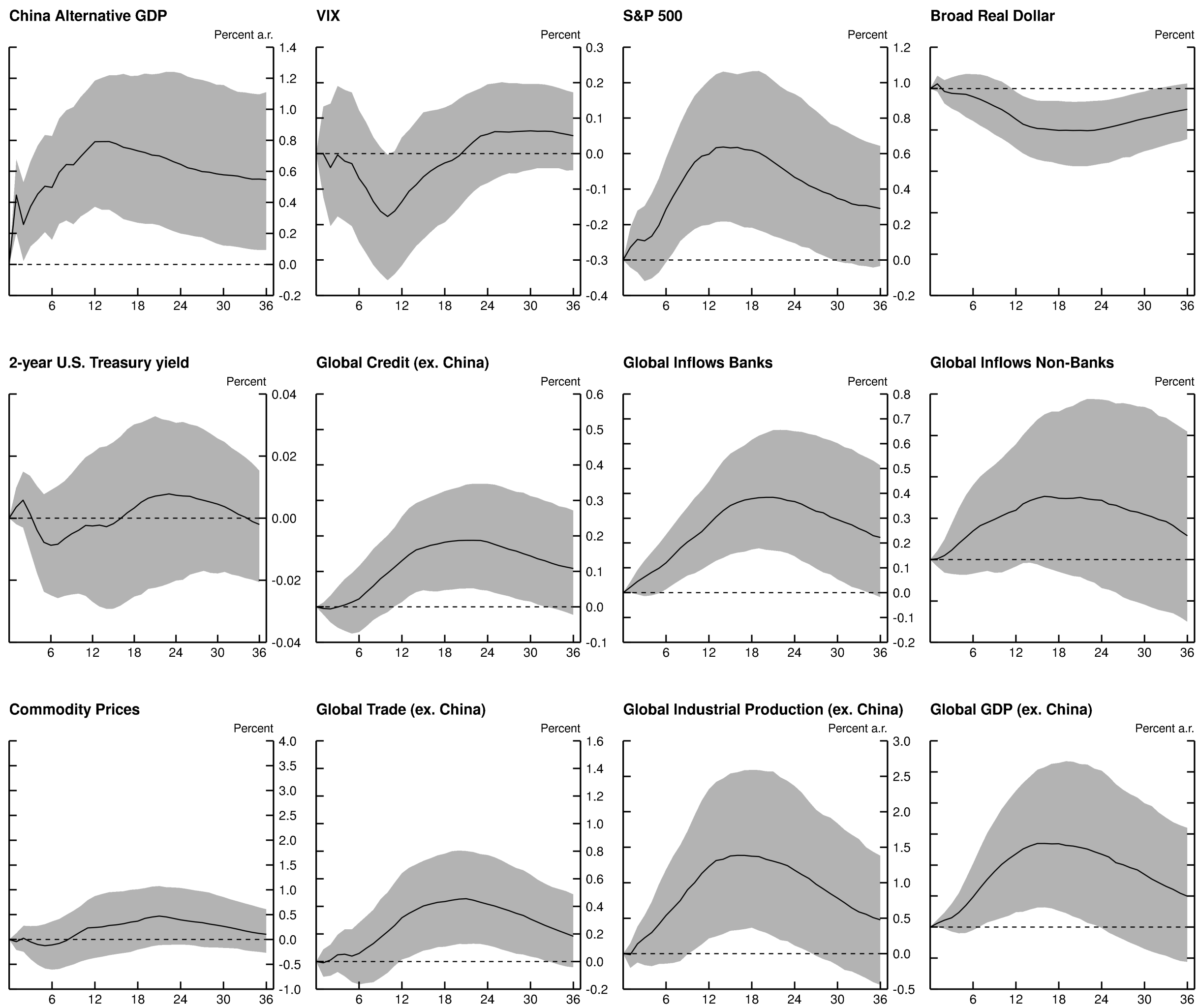



FIGURE C.3: IMPULSE RESPONSES TO A CHINESE CREDIT IMPULSE SHOCK (2000-2019)

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2000 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.

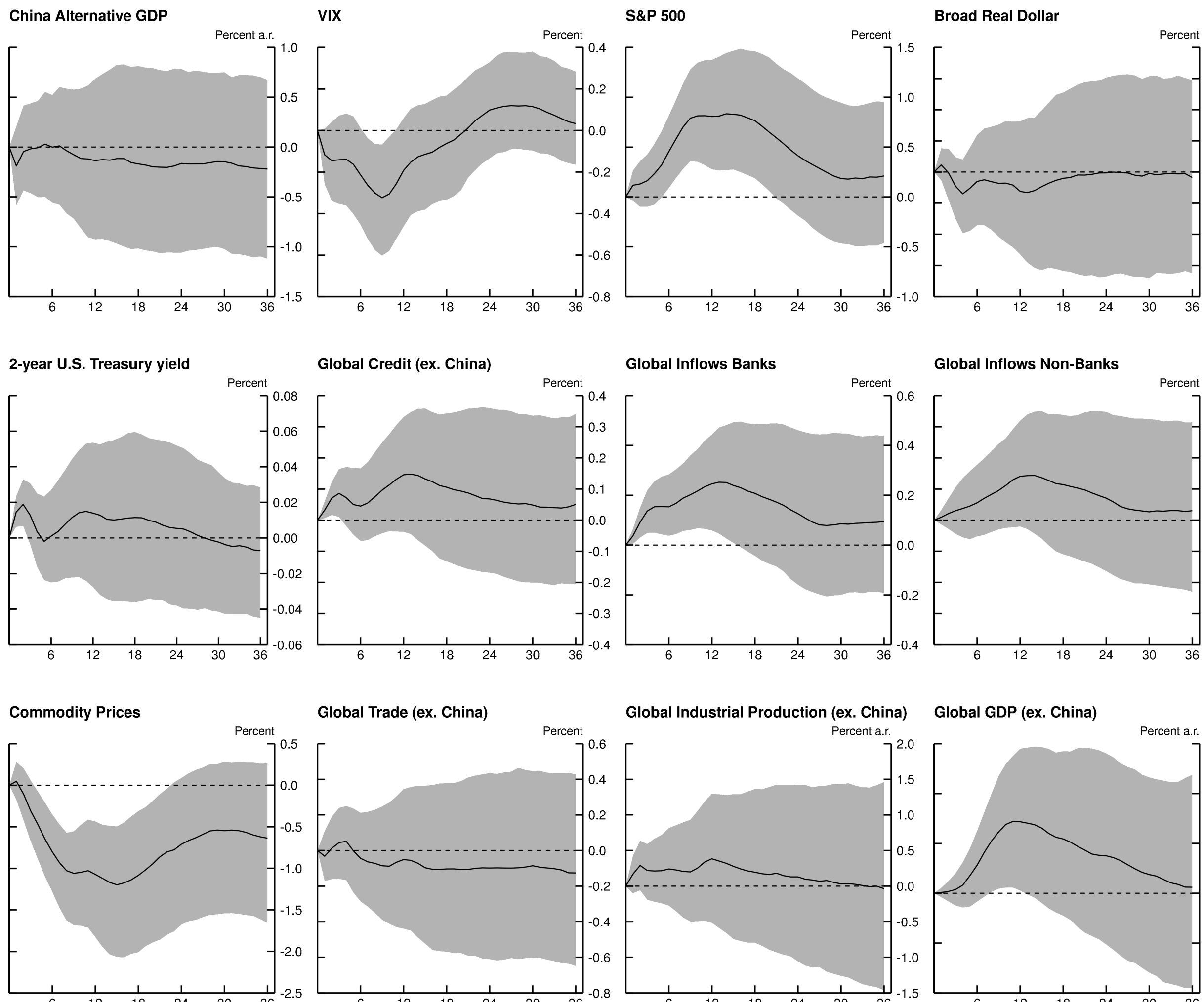



Figure C.4: Impulse responses to a Chinese Credit Impulse Shock (2000-2007)

Note: The black lines are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2000 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.

### C.3 Additional Robustness Results

The results in section 5.3 underscored the importance of using our alternative GDP measure in our VAR estimation. We show that an unexpected shock to China's credit impulse does not significantly affect China's official real GDP, which is counter intuitive and likely reflects the issue that China's official real GDP is overly smooth in the period following GFC. However, official Chinese real GDP is at the quarterly frequency and to estimate our benchmark VAR, we interpolated the quarterly to a monthly frequency using industrial production, which introduces potential measurement error. Therefore, as a robustness check, we use Chinese industrial production instead of real official Chinese GDP. As highlighted before, Chinese official industrial production is highly correlated with Chinese official real GDP and, therefore, also exhibits the smoothness property[36].

As illustrated in figure C.5, we show that a policy-induced expansionary credit impulse shock of 1% of China's GDP does not significantly affect China's official industrial production. This is similar to the results in figure 6, which is again puzzling and counter intuitive. However, China's credit policies do have a positive and significant effect on global financial conditions and economic activity through higher Chinese demand for goods and commodities. This result reflects that, as is the case for GDP, Chinese official industrial production is likely to be overly smooth and does not capture underlying manufacturing fluctuations. It follows that using China's official industrial production in our VAR also masks the impact of China's credit policies on its own economy, underscoring the importance of using an alternative measure for economic activity.

Finally, we further study the importance of using the credit impulse to identify Chinese demand shocks. We perform a similar exercise as in section 5.4, but now we take advantage of the monthly frequency to identify a unit shock to China's industrial production and evaluate its global spillovers. Figure C.6 illustrates that a unit shock to China's industrial production has limited spillovers to the rest of the world. Outside of an increase in asset prices, we barely find significant effects on the global financial cycle. Even though we do find positive and significant spillovers to global industrial production and GDP excluding China, there is no evidence for channels of transmission through higher Chinese demand for commodities or higher global trade outside of China, in sharp contrast to our main results. Altogether, using shocks to Chinese IP would suggest that the Chinese economy has no spillovers to the global financial cycle and muted spillovers to the global business activity. This is in sharp contrast to our benchmark results and highlight the importance of using China's credit impulse to identify policy-induced demand shocks to study global spillovers.

[36] See appendix A for more detail.

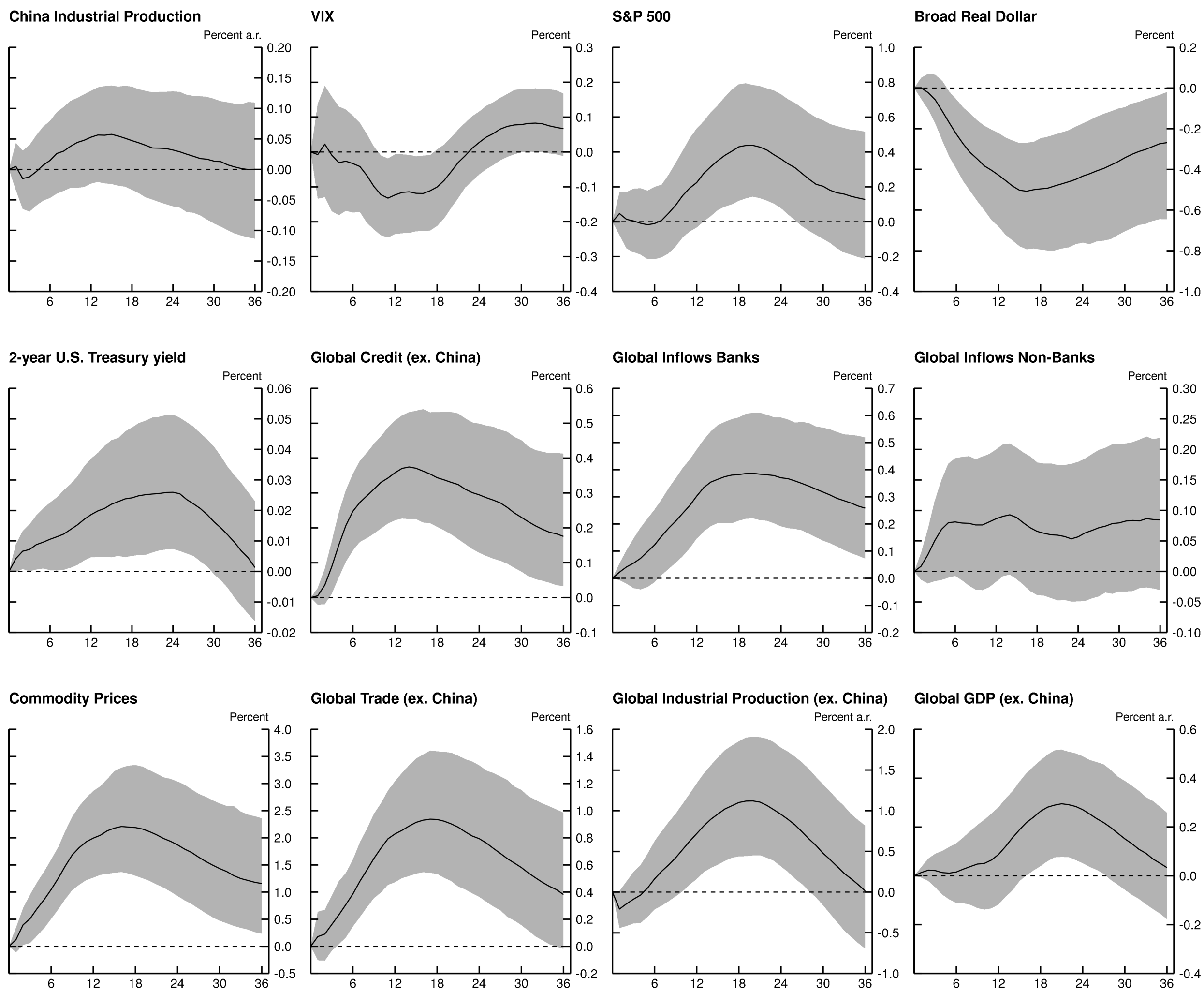



Figure C.5: Impulse Responses to a Chinese Credit Impulse Shock with Chinese IP

Note: The black lines in figure C.5 are the estimated impulse responses to a Chinese credit impulse shock of 1% of GDP and correspond to the posterior median estimates. The VAR is estimated from January 2011 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 C.1 for the VAR specification.

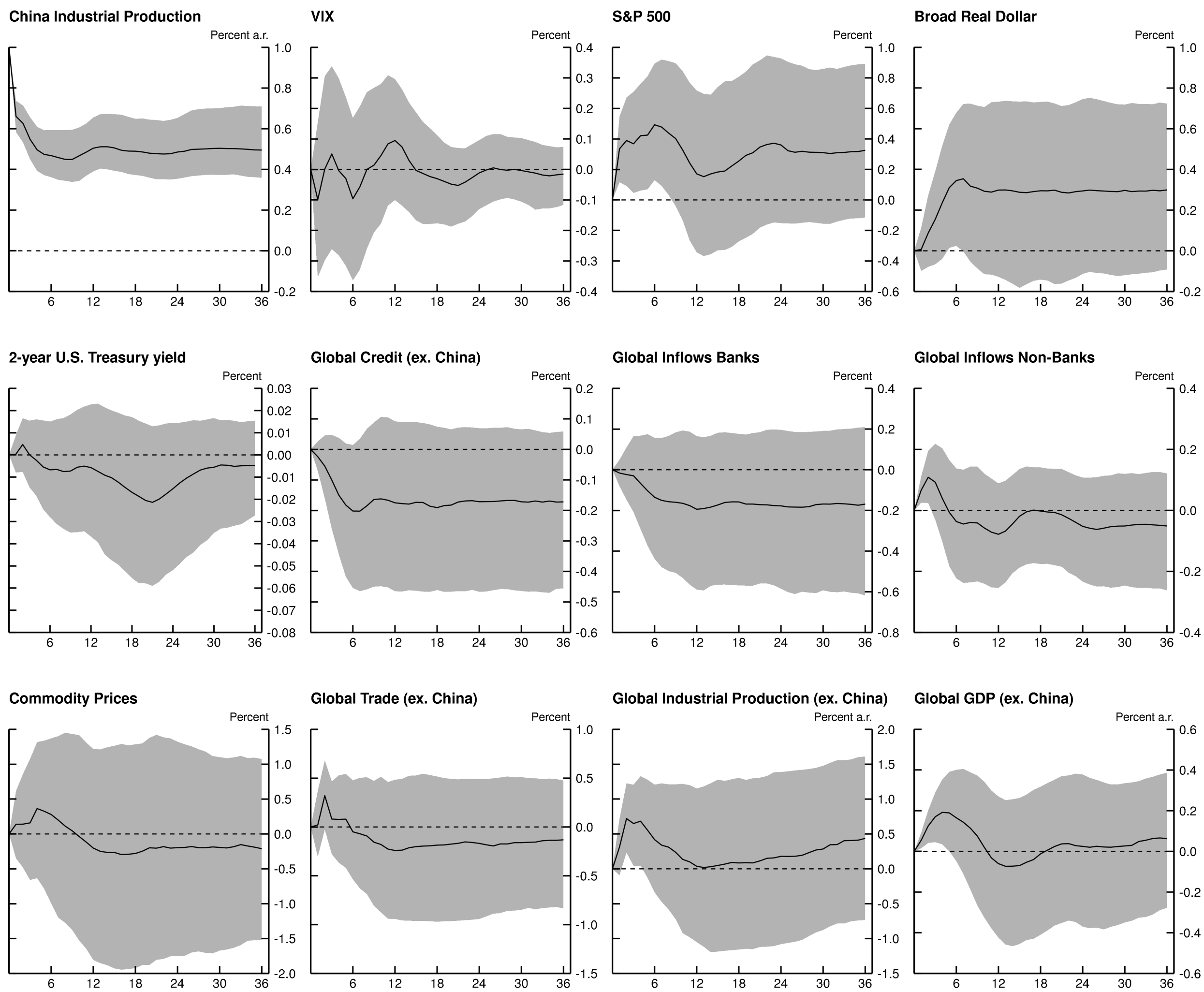



Figure C.6: Impulse Responses to a Chinese IP Shock

Note: The black lines in figure C.6 are the estimated impulse responses to a unit shock to Chinese official industrial production and correspond to the posterior median estimates. The VAR is estimated from January 2011 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 C.1 for the VAR specification.

# Appendix D: Mathematical Appendix

## D.1 Structural Break Test on China's GDP Volatility

We test for the possibility of a structural break in China's GDP volatility following the procedure proposed by McConnell and Perez-Quiros (2000). Formally, the procedure consists of testing for a structural break in the residual variance of 4-quarter Chinese GDP growth, defined as

$$\Delta y_{t,t-4} = \mu + \Phi \Delta y_{t-1,t-5} + \epsilon_t. \tag{D.1}$$

If $\epsilon_t$ follows a normal distribution, then $\sqrt{\frac{\Pi}{2}}|\hat{\epsilon}_t|$ is an unbiased estimator of the standard deviation of $\epsilon_t$. We test the null hypothesis of no break in the standard deviation through the following equation with a single intercept ($\alpha$)

$$\sqrt{\frac{\Pi}{2}}|\hat{\epsilon}_t| = \alpha + s_t \tag{D.2}$$

against the alternative with two intercepts ($\alpha_1$ and $\alpha_2$)

$$\sqrt{\frac{\Pi}{2}}|\hat{\epsilon}_t| = \alpha_1 D_{1,t} + \alpha_2 D_{1,t} + s_t, \tag{D.3}$$

where

$$D_{1,t} \begin{cases} 1 & \text{if} \quad t \leq T \\ 0 & \text{if} \quad t > T \end{cases} \qquad D_{2,t} \begin{cases} 0 & \text{if} \quad t \leq T \\ 1 & \text{if} \quad t > T \end{cases}, \tag{D.4}$$

and $T$ is the estimated structural break for the two standard deviation estimations $\alpha_1$ and $\alpha_2$.

We perform a Wald test $F_n(T)$ recursively over the sample $n$ from $T_1 = 0.15 \times n$ to $T_2 = 0.85 \times n$, and select the estimated break point $T$ that maximizes $F_n(T)$, as in

$$\sup_{T_1 \leq T \leq T_2} F_n = \sup F_n(T). \tag{D.5}$$

Over the sample 1992:Q1 to 2019:Q4, the null hypothesis of no structural break in the standard deviation of China's GDP growth is rejected at a 1% significance for all periods since 2007:Q1, as presented in D.1. Moreover, following the test described by equation D.5, the point with the highest $F_n(T)$ is 2010:Q3, indicating the most likely structural break point in China's GDP volatility.

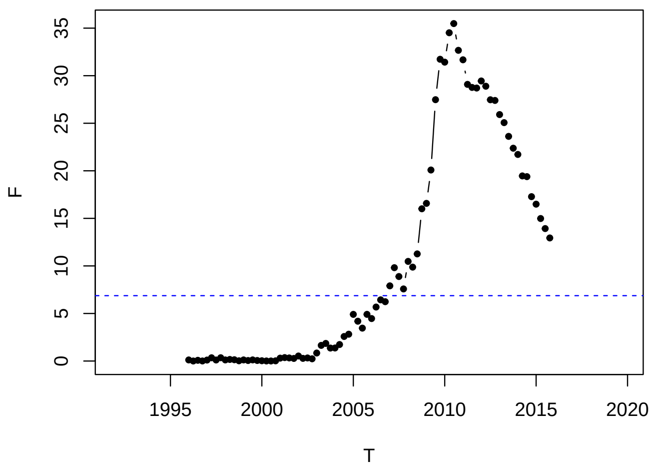



FIGURE D.1: F-STATISTICS FROM A STRUCTURAL BREAK TEST ON CHINA'S GDP GROWTH VOLATILITY

Note: Figure D.1 plots the F-statistics from a rolling Wald test for a structural break in the volatility of China's real GDP growth. The blue dashed line is the critical value corresponding to the 99$^{\text{th}}$ percentile of the $F_{1,110}$ distribution.