The Hidden Dragon: China's Contribution to the Global Cycle*

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Abstract

China's economy accounts for 16% of world GDP and has contributed on average more than 30% to global growth in recent years. Yet, China's role as a driver of the fluctuations in the global economy has been largely unexplored, possibly because its official GDP is seemingly uncorrelated with the global cycle. In this paper, we quantify the role of China's economy in driving the global cycle. Specifically, we estimate the impact of China's credit policies on global economic activity and commodity prices. To do so, we first construct measures of China's credit impulse and GDP growth that better capture the volatility of underlying Chinese economic activity. We then estimate a Structural Vector Autoregressive Model (SVAR) to estimate the impact of movements in Chinese economic activity induced by China's domestic credit stimulus on economic activity in the rest of the world. Our results show that China's credit policies since the Great Financial Crisis have played an important role in supporting economic growth, not only in China but also globally. We find that shocks to China's credit policies explain 15% of the movement in world industrial production and 21% of global commodity price movements over two years, which highlights China's importance in contributing to the global cycle.

JEL classification: C52, E50, F44
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1 Introduction

Decades of sustained rapid growth have transformed China's economy and, with it, the global economic landscape. In 1990, China's economy, valued at market exchange rates, represented only 2 percent 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 percent of global GDP, making it the second largest economy in the world behind the United States. Moreover, China's contribution to global *growth* has surged from less than 10 percent in the 1990s to 34 percent in the 2010s.

With China's integration into the global economy, Chinese demand is increasingly cited as an important driver of the global business cycle. After the Great Financial Crisis (GFC), China's 'open-the-floodgates' credit stimulus was cited as playing a prominent role in the recovery of the global economy, especially in emerging market economies. Conversely, China's policies to rein in credit growth in 2014-2015, and again in 2017-2019, dampened Chinese demand and featured prominently in many accounts as a key driver of slower growth abroad. For instance, companies like Apple and Caterpillar downgraded their sales outlook citing weak Chinese demand, while European car companies were hurt by plummeting auto sales in China. In addition, declines in commodity prices were attributed in large part to slowing growth in China.[1] Despite this anecdotal evidence, there are few quantitative estimates of China's independent contribution to fluctuations in global growth. This is what we set out to provide in this paper.

Several problems arise in analyzing the relationship between Chinese and global growth. The first is that there are longstanding concerns about the quality of China's GDP data (Chen et al., 2019). A particular concern for our study is that Chinese GDP is widely believed to be overly smooth (Nakamura et al., 2016; Clark et al., 2018; Fernald et al., 2020), a problem that has become especially acute in recent years. This observed smoothness in official GDP could mitigate or even mask the transmission of a Chinese shock to the rest of the world. The second problem in estimating this relationship is that, as a major exporter, China is a recipient of shocks from, as well as a source of shocks to, the rest of the world.

In this paper, we address these concerns in two ways. First, we estimate an alternative measure of China's real GDP using a large set of indicators of economic activity that we believe are less subject to smoothing by the government, including property market data, auto sales, reported

[1] In addition to weaker Chinese demand, the slowdown in global growth has been attributed to trade policy uncertainty (Caldara et al., 2019), a more broad-based global slowdown in the automobile sector, and the downturn in the tech cycle in Asia (IMF, 2019). That said, in each of these explanations, China plays a central role.

imports from other countries, satellite nighttime lights data, and pollution data. To construct an alternative GDP measure from these series, we employ a dynamic factor model (DFM), which is able to flexibly handle series of different lengths and frequencies, and has become an increasingly important tool for nowcasting a wide set of macroeconomic variables.

Second, to isolate the effect of China-induced policy shocks on the global economy, we take advantage of the fact that the Chinese authorities exert a significant degree of direct control over the supply of credit to the economy. To that end, we construct a measure of the Chinese credit impulse, which is an aggregate of different types of credit directly influenced by the Chinese authorities, including bank loans, shadow credit, and local government bonds. We then use shocks to China's credit impulse in a vector autoregression (VAR) to identify the impact on Chinese growth and its transmission to the rest of the world. This approach is preferred to directly estimating the impact of Chinese GDP on global activity, as movements in Chinese GDP could be endogenous to the global cycle.

Our paper contributes to the literature in two ways. First, our alternative measure of Chinese GDP growth and of the credit impulse should facilitate research on the Chinese economy, which is hampered by a lack of suitable data. Second, to the best of our knowledge, this is the first paper that uses an alternative growth indicator for China to estimate the impact of fluctuations in Chinese demand on global activity.

Our results show that China's credit policies since the Great Financial Crisis have played an important role in supporting economic growth, not only in China but also globally. We find that China's credit policies explain 15 percent of the variation in global industrial production and 21 percent of movements in global commodity prices, highlighting the importance of China's role in the global cycle. Additionally, we find that including our alternative measure for Chinese GDP is important in explaining the transmission of Chinese growth shocks to the rest of the world. Specifically, the VAR results show that an unexpected increase in the credit impulse generates an immediate increase in Chinese GDP growth, which in turn leads to an increase in global commodity prices and global industrial production.

The remainder of the paper is organized as follows. Section 2 places our paper in the context of the recent literature. Section 3 describes how China's economy has transformed the global landscape in the past decade. Section 4 describes the estimation of the alternative growth series for China and the data series we use. Section 5 describes the quantitative analysis. Sections 6 presents the results. Section7 presents several robustness exercises. Section 8 concludes.

2 Literature

This paper contributes to three main strands of the literature. The first is the literature on global business cycle co-movements. The second is the measurement of Chinese GDP and with that the usage of using Dynamic Factor Models (DFM) to forecast macroeconomic variables.

Global business cycle co-movements There is a vast literature on global cycles and studying the driving forces behind GDP co-movement across counties. One strand of the literature has focused on the role of financial integration. However, Kalemli-Özcan et al. (2013) find a strong negative effect of banking integration on output synchronization, conditional on global shocks and country-pair heterogeneity. Another strand of the literature has focused on common productivity shocks, with a focus on G-7 countries. Aruoba et al. (2011) find that a common real activity factor across G-7 countries, explains a significant amount of cross-country variation and tracks the major global cyclical events during the period from 1970s to the 2010s. Crucini et al. (2011) find a large common factor in oil prices, productivity, and the terms of trade. Their results show that productivity is the main driving force of international business cycles. In contrast, more recent work by Huo et al. (2020) finds that TFP shocks are virtually uncorrelated across countries, whereas non-technology shocks are positively correlated. Moreover, they find that these positively correlated shocks account for two thirds of the observed GDP co-movement, with international transmission through trade accounting for the remaining one third. This second observation fits in another strand of the literature of global business cycle co-movoments, which focuses on the role of trade (Baxter and Kouparitsas, 2005; Kose and Yi, 2001; Calderon et al., 2007; Liao and Santacreu, 2015). Specifically, Johnson (2014); Duval et al. (2015); de Soyres and Gaillard (2019, 2020) study the importance of trade in intermediate inputs as part of global value chains and how it contributes to global GDP co-movements. de Soyres and Gaillard (2019) find that GDP co-movement is significantly associated with trade in intermediate inputs but not with trade in final goods. Finally, recent work by Monnet and Puy (2019) studies global cycles for a wide set of emerging and advanced countries since 1950 and finds that real and financial cycles are generally driven by shocks that originate in the United States. That said, China is not part of their analysis and, more generally, the role of China remains in large part unexplored. Our paper contributes to this literature by quantifying China's role in driving the global cycle using China's credit policy shocks. Also, our results are complementary to Fernández et al. (2020), which shows 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.

We in fact find that China's credit policies since the GFC have contributed to 21 percent to global commodity price fluctuations.

Chinese GDP Measurement The accuracy of China's official growth has been a long standing concern. Consequently, researchers have estimated a host of 'alternative indicator models' to better capture the underlying state of the Chinese economy. These alternative indicators models can be broadly classified in two categories. There is one strand that uses data series, which are reported by the Chinese authorities and another that uses a mix of officially reported data series and other data series that are not released by the Chinese government.

One well-known alternative measure is the Li Keqiang Index, proposed by the current vice premier Li Keqiang. This index weights three 'alternative' data series: (1) railway cargo volume, (2) electricity consumption, and (3) bank loans, which are weighted by 20%, 40%, and 40%, respectively. One issue is that the index is quite skewed towards the manufacturing sector and therefore might not capture well the services sector, which has grown notably in importance in recent years.

More recently, several other paper have estimated alternative indicator models using different data sources and methodologies. Using Chinese micro survey data, Chen et al. (2019) document discrepancies between the sum of local GDP and national GDP. They trace most of the discrepancy back to the locally reported figures for industrial production, and they use value added tax revenue data to adjust these data and construct a new national GDP. The authors find that nominal GDP growth for 2008-2016 has been overstated by 1.7 percentage points, mostly through inflation of industrial investment growth figures.

Morris and Zhang (2019) uses Nitrogen Dioxide (NO_2) as a way to measure economic activity and compare their result from sub-national regions within China to officially reported data. The paper shows that while for many sub-regions within China, the NO_2 data corroborates the official GDP data during the Great Recession period. The authors also find that for the 2015 episode, the NO_2 data does not support the official for certain sub regions and they claim that this is the result of these sub-regions misreporting their data.

Fernald et al. (2020) use foreign-reported exports to China and Hong Kong as a better measure of Chinese economic activity instead of official real GDP growth. They then perform a principal component analysis on several Chinese data series to best explain their preferred measure of Chinese economic activity. The alternative measure is the first principal component of a set of eight Chinese indicators: consumer expectations index, electricity production, exports, fixed asset investment, floor space started, industrial production, rail freight carried, and retail sales. They show that their alternative GDP measure is more volatile than officially reported but they find that China's detrended GDP in more recent periods is higher than officially reported. Similarly, Clark et al. (2018) also estimate an alternative growth series for China using nighttime lights data. They find that growth during the 2015 slowdown might be more pronounced than officially reported. These findings seem consistent with Nakamura et al. (2016) who document this smoothness in official GDP and inflation for an earlier time period from 1995 to 2011. In this paper, we build on this literature by proposing and estimating a new alternative growth series that better captures underlying economic activity in China with a wider set of data variables.

Dynamic Factor Models (DFM) In this paper, we estimate a new alternative growth series for China using a Dynamic Factor Model (DFM) following the seminal paper by Giannone et al. (2008). The use of DFMs has become an increasingly important tool for nowcasting a wide set of macroeconomic variables. Traditionally, DFMs have been used for nowcasting countries' GDP (Barhoumi et al., 2010; Matheson, 2010; Luciani and Ricci, 2014) or regional GDP (Bańbura and Modugno, 2014; Camacho and Perez-Quiros, 2010; Cascaldi-Garcia et al., 2020). That said, DFMs have been increasingly used to nowcast a wide set of other macroeconomic variables including inflation (Modugno, 2013), and trade (D'Agostino et al., 2017). We contribute to this literature by estimating a DFM for China similar to Yiu and Chow (2010) and Giannone et al. (2013) but using a wider and different set of variables and for data up until 2019.

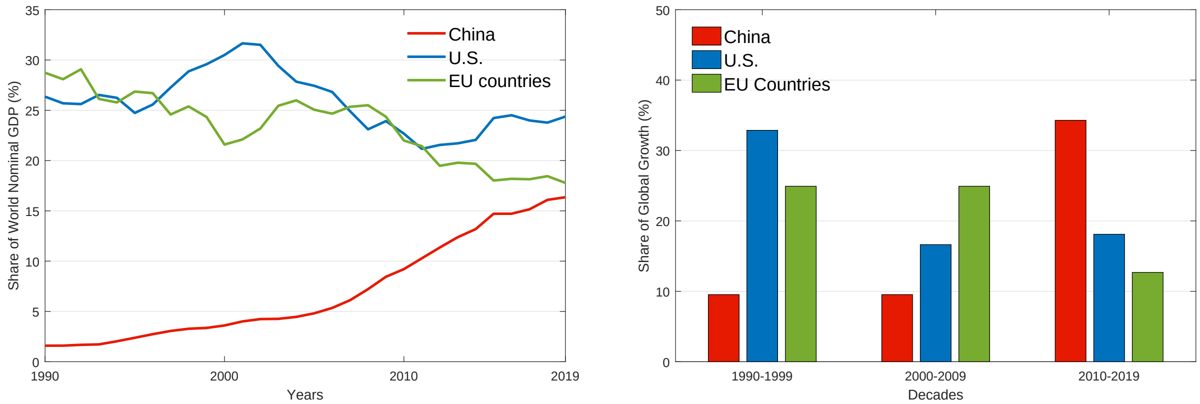
3 China's changing role in the global economy

In this section, we present several stylized facts to document China's changing role in the global economy over the past three decades. We then contrast China' surging role as a global consumer to the apparent disconnect between its official GDP and the global cycle.

Fact 1: China's footprint in the global economy has surged

Decades of sustained rapid growth have transformed China's economy and, with it, the global economic landscape. Figure 1a plots Chinese GDP, valued at market exchange rates, as a share of global GDP. In 1990, China's economy represented only 2 percent 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 percent of global GDP, making it the second largest economy in the world behind the United

Figure 1: China's footprint in the global economy



(a) Share of global GDP (%) (b) Share of global growth (%)

States, which represents about 24 percent of global GDP.[2] Moreover, as figure 1b shows, China's contribution to global *growth* has skyrocketed from less than 10 percent in the 1990s to 34 percent in the 2010s, which is higher than the growth contributions of the U.S. and the EU combined.[3]

Fact 2: Chinese growth has become less export dependent

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 2. China's exports as a share of its GDP surged from about 20 percent in the 1990s to over 30 percent during the 2000s. Similarly, the value added in Chinese exports as a share of GDP also surged from about 17 percent in the 1990s to about 25 percent during the 2000s.

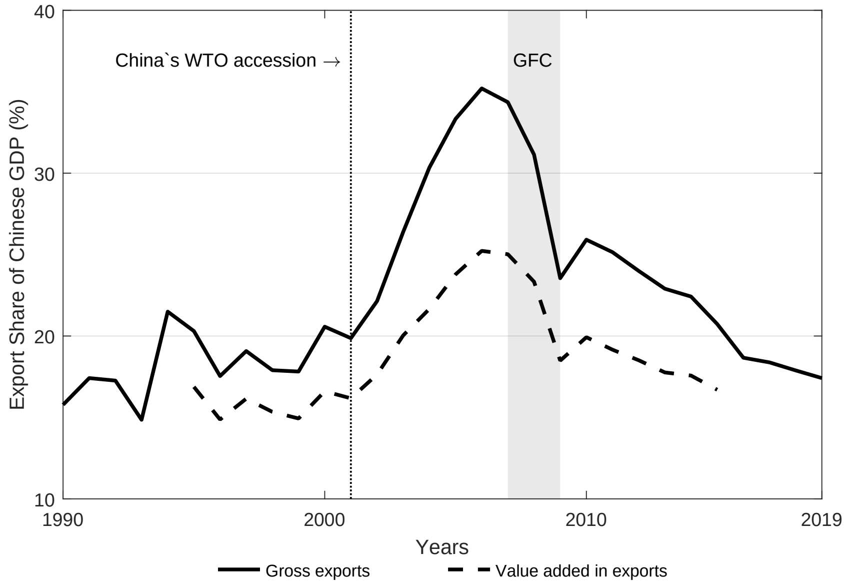
That said, figure 2 also highlights that the export contribution to China's GDP has declined notably in the 2010s. Indeed, the collapse of external demand during the GFC in 2008 and the anemic recovery in advanced economies that followed, meant that China could no longer rely on exports to sustain rapid growth.[4]

[2] Similarly, China's contribution to real global GDP has soared from 2 percent in 1990 to 13 percent in 2018. That said, on a purchasing power parity basis, China's economy has surpassed that of the United States. Specifically, China accounts for 19 percent of global GDP and the United States for 15 percent.

[3] We calculate the contributions to global GDP growth during each period as follows: $S_t = \frac{\sum_{n=0}^{2} D_{m-n}}{\sum_{n=0}^{11} Y_{m-n}} - \frac{\sum_{n=3}^{5} D_{m-n}}{\sum_{n=12}^{23} Y_{m-n}}$.

[4] The net export contribution of goods and services to real GDP growth has also fallen since the GFC as shown in figure A.3 in the appendix.

Figure 2: Export share of GDP (%)



Fact 3: Massive credit stimulus have supported domestic demand post GFC

In the aftermath of the GFC, the Chinese government responded with massive investment-oriented stimulus programs. To underscore this point, we construct China's credit impulse, defined by the the change in the flow of new credit as a percent of GDP.[5] What makes the construction of a credit aggregate difficult is that China uses different measures to supply credit to the real economy. In particular, in the period following the GFC, China's central bank, the People's Bank of China (PBOC) relied heavily on the usage of local government bonds to heavily invest in infrastructure products. Moreover, the PBOC sometimes changes its definition of total credit. Therefore, the first contribution of this paper is to construct a credit impulse for China that takes these issues into account. We define as aggregate credit as the PBOC's official total social financing less equity financing, plus local government bonds corrected for double counting of local government special bonds.

We plot China's credit impulse in figure 3. The figure highlights that in the period after the GFC, China "opened the credit floodgates" in order to stimulate the economy. Additionally, in

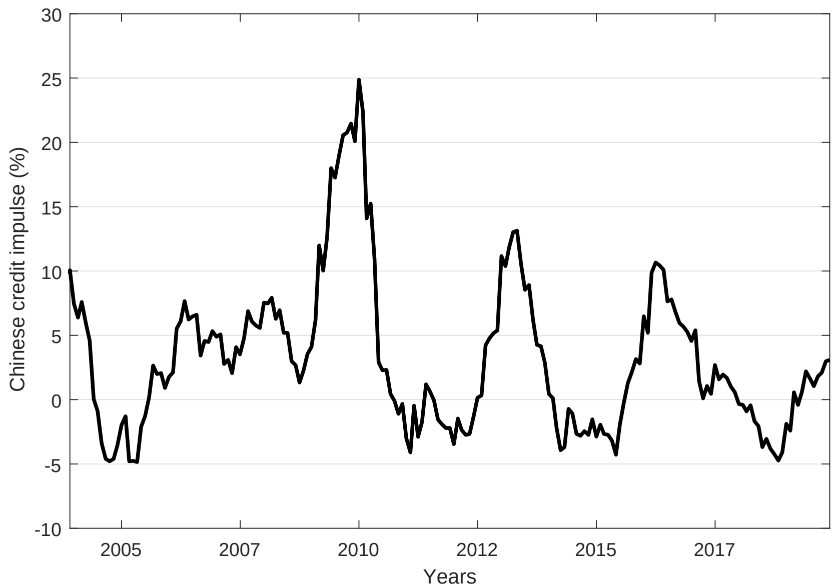
[5]More formally, the credit impulse is measured at the monthly frequency and is denoted by

$$CI_m = \frac{\sum_{n=0}^{2} D_{m-n}}{\sum_{n=0}^{11} Y_{m-n}} - \frac{\sum_{n=3}^{5} D_{m-n}}{\sum_{n=12}^{23} Y_{m-n}}$$

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

subsequent periods, Chinese authorities have actively used credit stimulus to boost the economy and in particular domestic demand.

Figure 3: China's credit impulse (%)



Fact 4: China's credit policies are highly correlated with the global cycle

As a result from these massive Chinese stimulus programs, Chinese growth has been increasingly supported by consumption. As figure 6a highlights, China's contribution of consumption to real GDP growth has grown over the past decade and now accounts for about 60 percent of real GDP growth in China.[6] With consumption being an increasingly driver of Chinese growth, its contribution to global consumption growth has also surged as shown in figure 6b. Before the GFC, China's household consumption growth only accounted for about 10 percent of global consumption growth. In the past decade, China's contribution has surged to about 30 percent.

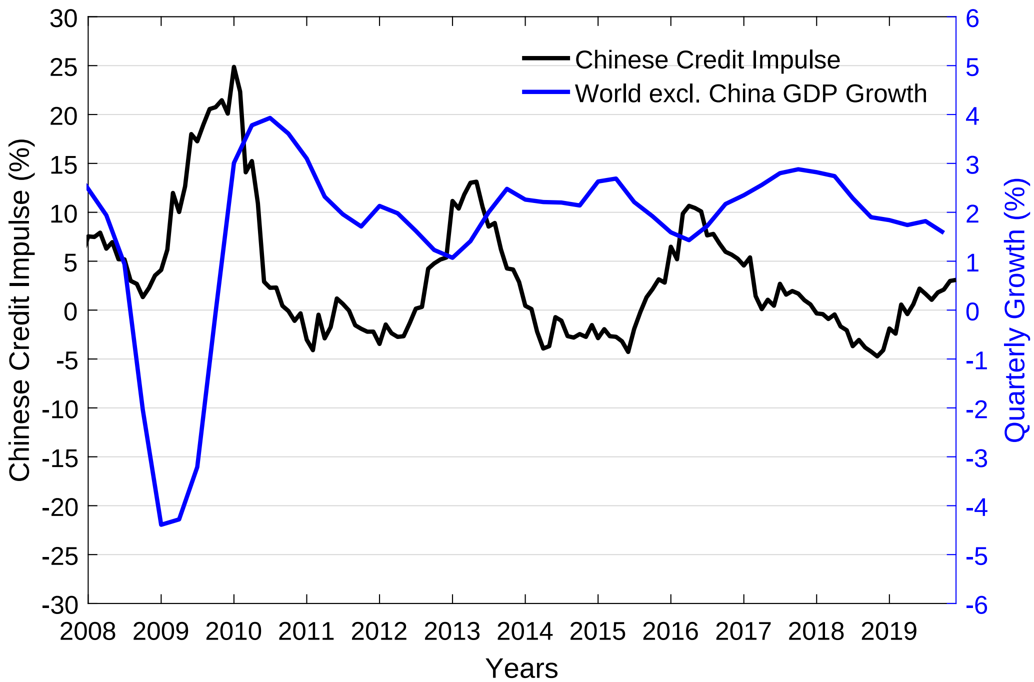
As such, Chinese demand, is increasingly cited as an important driver of the global business cycle. To highlight this, we plot China's credit impulse with quarterly growth rates of world GDP growth excluding China. After the Great Financial Crisis (GFC), China's 'open-the-floodgates' credit stimulus was cited as a prominent driver of the rapid recovery. Moreover, China's credit stimulus was also heavily cited as driving up commodity prices as shown in figure 5. Conversely, China's subsequent policies to rein in credit growth in order to reduce financial risks in the Chinese

[6] See figure A.3.

economy in 2014-2015 and more recently at the the end of 2016 dampened Chinese demand and featured prominently in many accounts as a key driver of slower growth and falling commodity prices.

Despite the fact that China figures prominently in many accounts of the drivers of fluctuations in global growth, there are still few quantitative estimates for China's contribution to the global cycle.

Figure 4: China's credit impulse and the global cycle



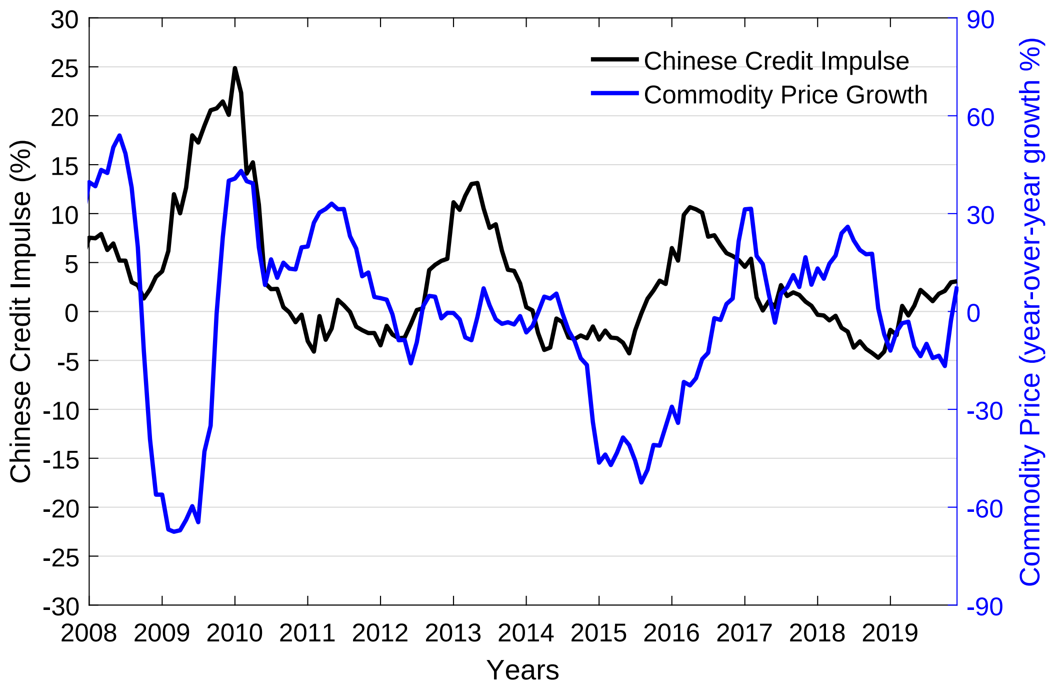
Fact 5: Yet, China's official GDP is uncorrelated the global cycle

Motivated by the former stylized facts, this paper studies China's role in driving the global cycle.[7] One major issue in quantitatively assessing this question is that China's data accuracy regarding its GDP is a longstanding concern.

Specifically, there is a concern that China's GDP is overly smoothed. This is has been a longstanding concern as highlighted by Nakamura et al. (2016), but has become even more apparent in recent years. As figure 7a shows, the volatility in China's GDP has fallen markedly over the past

[7]In this paper we focus on global commodity prices and manufacturing activity as services imports for China still remains a relatively small fraction of total imports. For instance, in 2018, goods imports accounted for about 80 percent of total goods and services imports.

Figure 5: China's credit impulse and global commodity prices



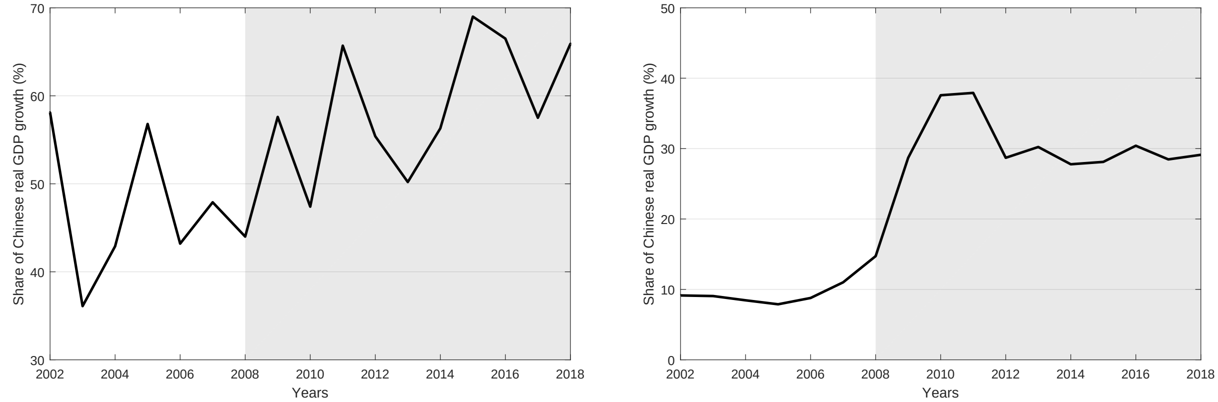
decade, and especially in recent years. Research by Fernald et al. (2020) and Clark et al. (2018) provide evidence that official Chinese growth is seemingly more smooth than measured underlying economic momentum. Therefore, using China's official GDP growth to study its role in the global cycle might mitigate or mask the estimated transmission from China's economy to the world. In fact, figure 7b, which plots real GDP growth for China and the rest of world, highlights exactly this issue. It shows that despite China's integration in the global economy, the co-movement between Chinese and global GDP growth has declined. As shown in Figure 7b, Chinese GDP growth was reasonably well correlated with global growth even after the GFC. In more recent years, however, that correlation has fallen notably, with Chinese growth holding relatively steady along a declining path despite substantial volatility in global growth.[8]

In fact, when comparing the volatility of Chinese de-trended GDP to all countries over time in history, as presented in figure 8, one finds that China's GDP volatility's is among the smoothest compared to all other countries. Additionally, in more recent years, that volatility if the lowest in China's own history and in all countries' history.

Therefore, in this paper, we estimate an alternative measure of China's real GDP using a dynamic factor model (DFM) as described in the next section.

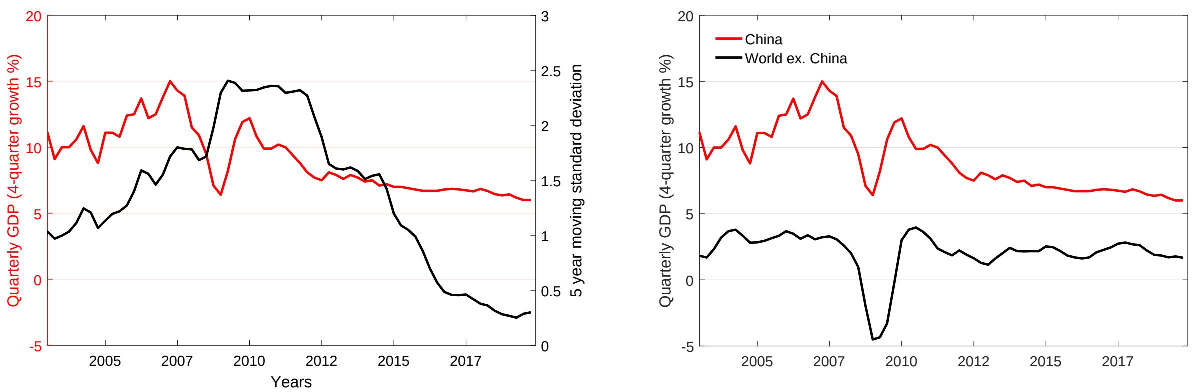
[8]Similarly, figure A.2 in the Appendix shows that the same pattern holds for industrial production.

Figure 6: Chinese increasing consumption



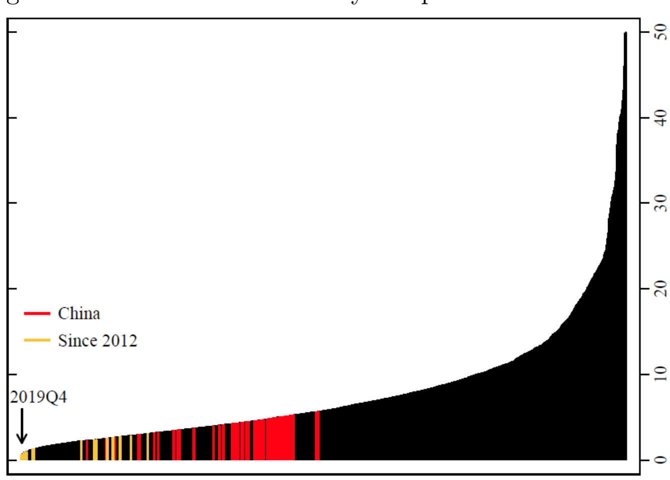
(a) Consumption share of China's real GDP growth (%) (b) China's share of global consumption growth (%)

Figure 7: China real GDP growth volatility



(a) China's real GDP growth and stdev. (b) China's and World ex. China's real GDP growth

Figure 8: China's GDP volatility compared to other countries



Note: Bars show standard deviations of changes in seasonally adjusted q/q real GDP growth rates for overlapping 5-year growth spells across 101 countries for which at least 5 years of quarterly data is available. Values greater than 50 are omitted.

4 Estimation

4.1 Dynamic Factor Model

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

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

while factors are defined by the transition equations

$$\mathbf{f_t} = \mathbf{A_1 f_{t-1}} + ... + \mathbf{A_p f_{t-p}} + \mathbf{u_t}. \tag{2}$$

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

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

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

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

4.2 Data

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

The first issue is that certain data series are highly correlated with official GDP growth. Therefore, these series are likely also smoothed. Particularly, we find that industrial production and retail sales are highly correlated with official GDP and if we estimate a DFM with those factors, our alternative GDP series resembles the official GDP growth series very closely. In addition, Chen et al. (2019) also find issues with industrial production data. Therefore, in a robustness analysis, we will exclude those series in.

The second issue is that China's economy has undergone a structural structural shift from an investment-led and export dependent country to a more consumption based country as described in the section 3. Consequently, to reflect underlying growth, our estimation needs data series that reflect those parts of the economy. We do so by including series such as semiconductor production, mobile phone production, auto sales, and property market starts. As highlighted earlier, a number of these series have relatively short time spans compared to more manufacturing based series. Therefore, the benefit of the DFM estimation method is that the method allows for including series that do not go all the way back.

Finally, the last issue is that in order to measure the underlying growth, we also needs to estimate the trend of economic growth is in the economy. This issue is especially important in the context of China, where trend growth has declined notably from about 10 percent in the period before the Great Financial Crisis and then has trended down to about 6 percent in more recent years. To address this issue we perform different types of analyses. We first assume that official trend growth is correct. Second we estimate two separate DFMs where one estimates the trend and the second the cycle. Finally, we perform some robustness checks where we assume trend growth is lower than officially reported.

Therefore, we will use a combination of: (1) traditional Chinese series, (2) Chinese series believed to be 'less smoothed' used in other papers including Fernald et al. (2020), (3) Chinese series, believed to be 'less smoothed' considered in this paper to better capture consumption in China, and (4) series from non-Chinese agencies. The series we consider include:

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

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

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

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

4.3 Alternative growth

Our preferred model uses a wide set of all previously described series.[9] In section 7 we consider additional specifications. To estimate our alternative growth measure we do the following steps:[10]

1. We use series in 12-month growth rates;[11]

2. We estimate the DFM from 2009 to 2019;

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

[10] We preform numerous robustness test that relaxes some of the underlying assumptions in these steps.

[11] The exceptions include PMI series and consumer confidence index, which are used in levels. We chose to estimate the DFM in 12-month changes because China's data series are predominantly reported in year-on-year changes as opposed to typical level series.

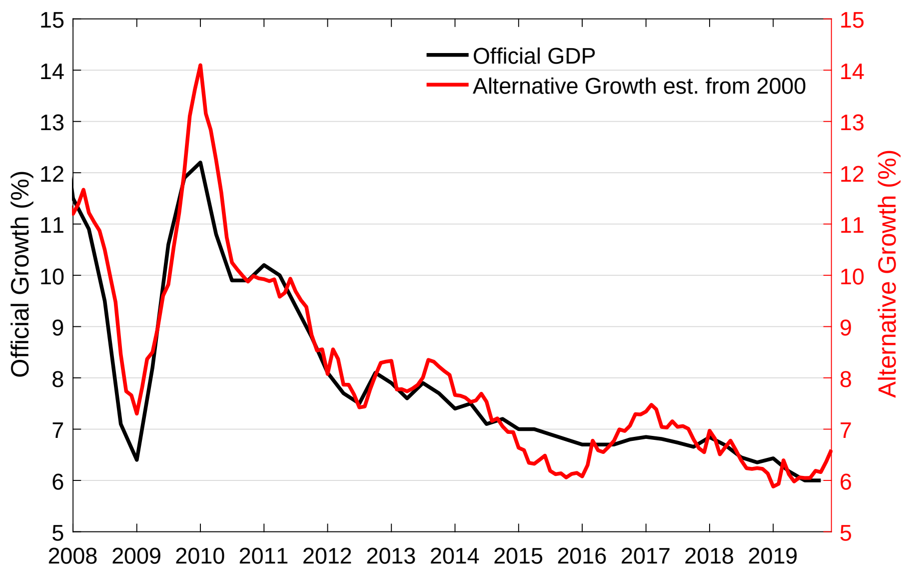
3. We construct one factor;

4. We regress the growth rate of de-trended official GDP on the factor to convert the factor movement into GDP movements;

5. We add official trend growth back in. The underlying assumption is that trend growth is correct.

Figure 9 plots our estimated alternative Chinese growth series and compare to the officially reported growth. There are several takeaways. The first is that our estimated alternative growth captures the overall path of official growth relatively well. Specifically, the model matches well the GFC movements and the subsequent downturn following the GFC.

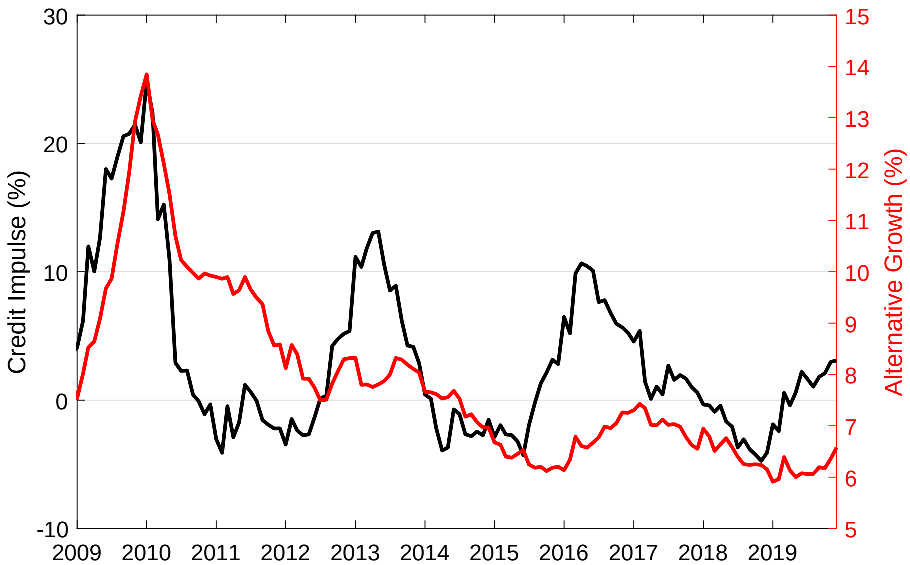
Figure 9: Alternative versus Official Growth



The second takeaway is that our estimated alternative growth is more volatile than official growth in recent years. More specifically, we find that the 2015 slowdown was more pronounced than officially reported. Specifically, we find that Chinese growth in 2015 slowed to 6%, which is 1 percentage point lower than officially reported. In addition, the stimulus induced recovery post-2015, pushed up our estimated growth measure more than reported. Our alternative growth estimate shows that Chinese growth rose to near 7.5 percent, whereas official GDP growth shows a growth rate of about 6.8 percent. Finally, the slowdown following the Chinese authorities' deleveraging campaign has caused growth to slow more rapidly than officially reported and dipped below official growth in the second half of 2018.

If we compare our alternative measure to the credit impulse, the impact of credit policies is more apparent as highlighted in figure 10. This is particularly striking because we have not included any credit measures in our DFM estimation such as household loans or banks loans. Even so, the credit impulse appears to lead our alternative growth indicator. This result motivates our analysis of how much China drives the global cycle as described in the next section.

Figure 10: Alternative Growth and the Credit Impulse



5 Quantitative Analysis

In this section we describe the analysis of the economic effects of a Chinese credit impulse. We estimate a monthly VAR that includes variables capturing the overall state of the global economy and Chinese variables, and evaluate the transmission effects of unexpected increases in the Chinese credit. The reason why we opt for a shock to China's credit impulse is that China has relatively more control over opening or closing the 'credit floodgates' than other economies. Therefore, this credit shock is akin to a fiscal shock. More importantly, by using this credit shock, we are able to better identify a Chinese demand shock. Indeed, if we would study the impact of a shock to Chinese growth using our alternative estimate, the impulse responses could just be an average of historical demand and supply shocks.

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

$$\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \epsilon_t. \tag{3}$$

Our benchmark VAR includes six endogenous variables: the VIX (VIX), which is an index of the implied volatility in S&P 500 stock index option prices from the Chicago Board Options Exchange (CBOE), a commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China ($DWIP$), the Chinese credit impulse ($DCRED$) and our alternative Chinese growth measure ($DYALT$) as described in the previous section. Additionally, we estimate a VAR with the same 5 main endogenous variables as in our benchmark model, that is, VIX DCP RUS $DWIP$ $DCRED$, but we use our estimated global factor from the DFM ($DYFAC$) to proxy for in Chinese growth. We estimate the second VAR to mitigate measurement error when mapping the global factor onto the trend growth of official Chinese GDP.

All variables are constructed in 12-month differences with the exception of the VIX and the 3-month U.S. Treasury bill, which are level series. The data frequency is monthly and, due to data availability, estimated with 12 lags and an intercept term, and with three subsamples: from January 2000 to December 2019, from January 2009 to December 2019, and from January 2012 to December 2019. We employ a Bayesian VAR in order to deal with the large number of coefficients by taking advantage of Minnesota priors (Litterman, 1986; Bańbura et al., 2010). Confidence bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution.

We identify a credit impulse shock through a recursive Cholesky decomposition in a block exogeneity structure, where the credit impulse is ordered first after all the global and foreign indicators. This structure assumes that an exogenous credit impulse shock can contemporaneously affect the Chinese economy, but its effects on the rest of the world are only observed with one-month lag. The ordering of the variables are defined as follows:

$$\mathbf{y}_t = \begin{bmatrix} VIX_t \\ DCP_t \\ RUS_t \\ DWIP_t \\ DCRED_t \\ DYALT_t \end{bmatrix}. \tag{4}$$

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

$$\mathbf{y}_t = \mathbf{B(L)u}_t. \tag{5}$$

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

$$\mathbf{u}_t = \mathbf{A}_0 \mathbf{s}_t \tag{6}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{7}$$

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.

6 Results

6.1 Impulse response functions

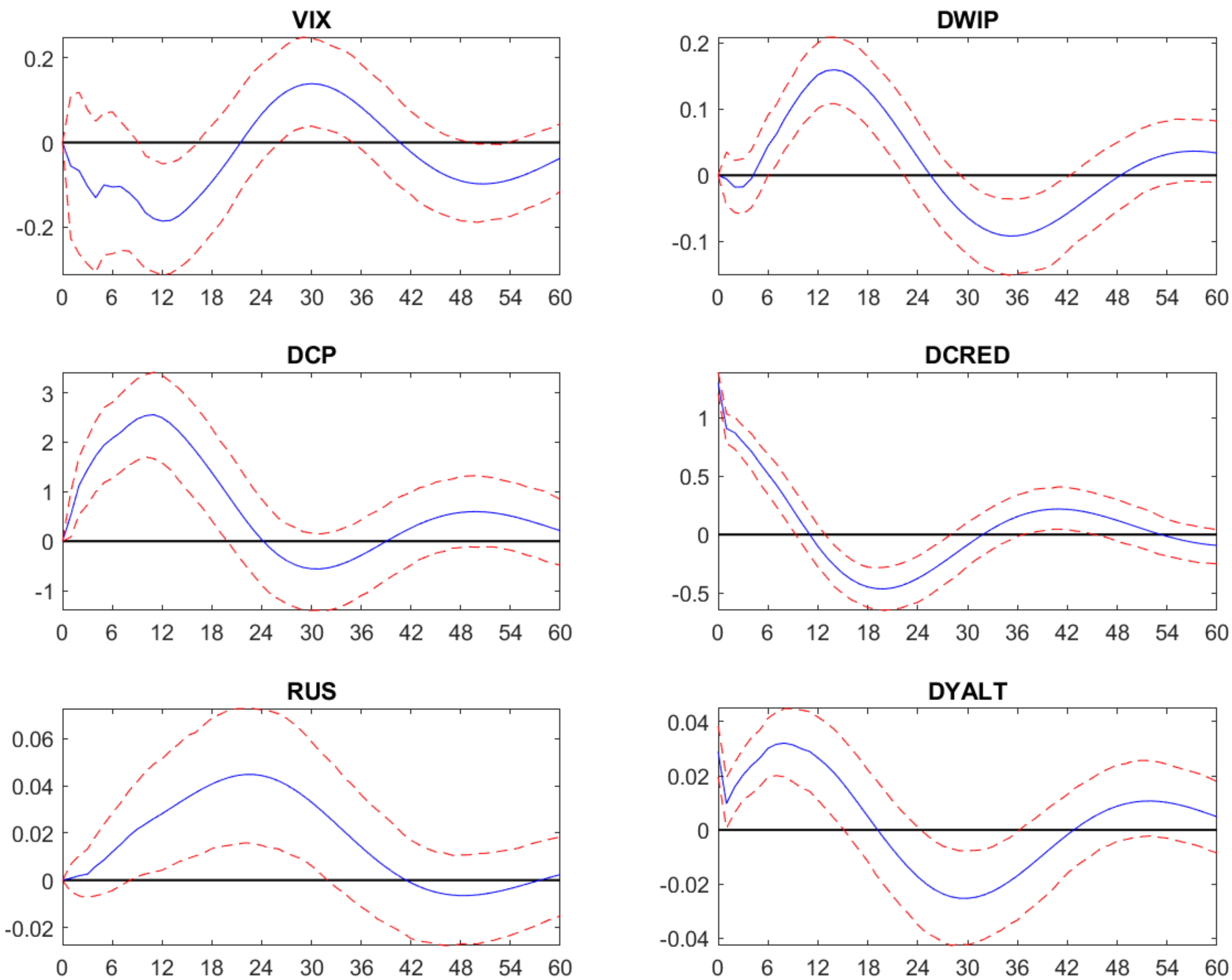
In this section we describe the results of the transmission of a credit impulse shock. This exercise allows us to evaluate the effects of the shock on the Chinese economy and its transmission to global activity. We first present the VAR results for our benchmark model focusing on the period after the Global Financial Crisis, from January 2012 to December 2019, when China's footprint in the global economy is largest. Next, we present the VAR results for the period from January 2000 to December 2019 to highlight how China's contribution to the global cycle has changed over the past decade.[12]

Figure 11 presents the impulse responses after an unexpected increase in the 12-month Chinese credit impulse of one standard deviation. We also include the 16th and 84th percentiles of the impulse response results from the draws from the posterior. By construction, the VIX, the U.S. interest rate measure and global industrial production excluding China do not react on impact. Chinese growth, proxied by our alternative growth measure, increases significantly on impact, with positive effects for about 12 months. This result highlights that China's credit policies constitute an important driver of Chinese growth.

Global industrial production (excluding China) also increases in the medium run, but with a lag compared to China's economic growth. While our estimated measure for Chinese growth peaks after around eight months, the global industrial production peaks only after around 15 months. This path indicates that the positive effects of the credit impulse are transmitted to the rest of the

[12] The benchmark VAR results for the period January 2009 to December 2019 are available in the appendix.

Figure 11: Economic responses to a credit impulse shock (2012-2019)



Note: The blue solid lines are the estimated impulse responses to a one standard deviation shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the VIX, commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China ($DWIP$), the Chinese credit impulse ($DCRED$) and our alternative Chinese growth measure ($DYALT$). The time period is from January 2012 to December 2019. The dashed red lines represent +/- one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior.

world, likely driven by a boost to global manufacturing. The delayed effect also indicates that the initial transmission direction is from from the Chinese economy to the rest of the world, and not the reverse where increased global demand boosts Chinese activity.

Our results also show that the credit impulse shock pushes up commodity prices notably, peaking around 12 months after the shock, and before the peak in the global industrial production. All told, our results show that China's credit policies since the Great Financial Crisis have played an important role in supporting economic growth in China and also globally.

Finally, we find that a positive shock to China's credit impulse decreases global uncertainty, proxied by the VIX, in the medium run and, after around 30 months, increases global uncertainty. The heightened uncertainty in turn induces a slowdown in the Chinese economy but also globally, before all variables converge back to the steady state after around three years. Once again, the deceleration in the Chinese economy leads the deceleration in the industrial production in the rest of the world, which is consistent with China's role in being an important driver of the global cycle.

Next, we present the VAR results when we use our estimated Chinese DFM factor instead of the alternative growth estimate. The reason we chose to present these results is that it alleviate the issue of (1) mapping the global factor onto actual de-trended GDP and (2) estimating trend growth.

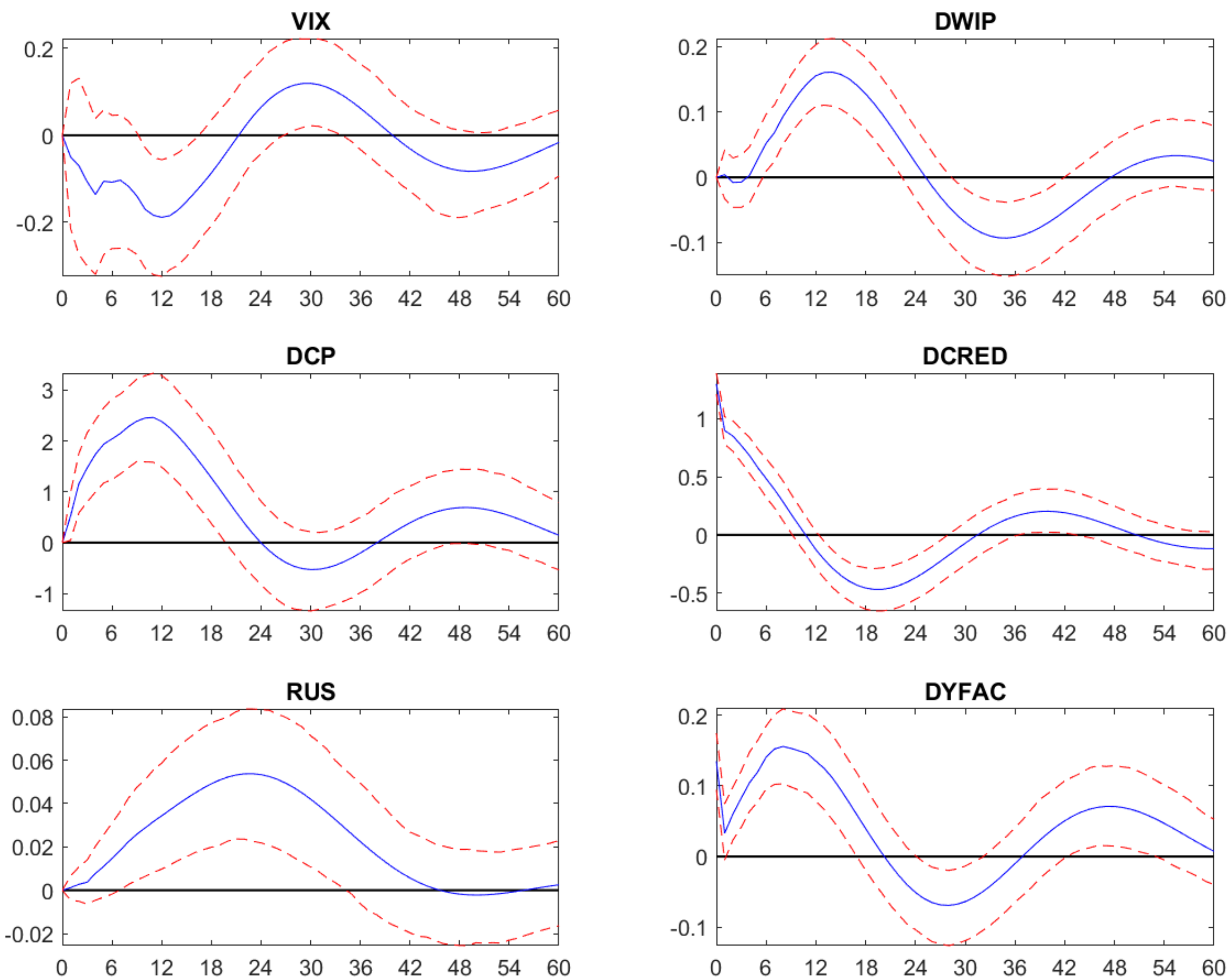
Figure 12 presents the impulse responses after an unexpected increase in the 12-month Chinese credit impulse of one standard deviation. The Chinese DFM factor rises and reaches its highest level after about 6 months, similar to our alternative growth estimate in figure 11. Additionally, the uncertainty surrounding the estimate is lower, which is consistent with the aforementioned two issues. Nevertheless, these results highlights that China's credit policies constitute an important driver of the Chinese economic activity.[13]

We find that global industrial production also increases, but again lags the upturn in the global factor. The delayed effect confirms that the initial transmission direction is from the Chinese economy to the rest of the world, and not the reverse. This supports the fact that China's credit policies have played an important role in supporting economic growth in foreign economies as transmitted by stronger Chinese growth. In terms of the other endogenous variables, we find very similar results to the analysis with the alternative Chinese growth.

Next, we present in Figure 13 the VAR results when we estimate the model for the period of January 2009 to December 2019 to include the GFC period. The impulse responses show that a one

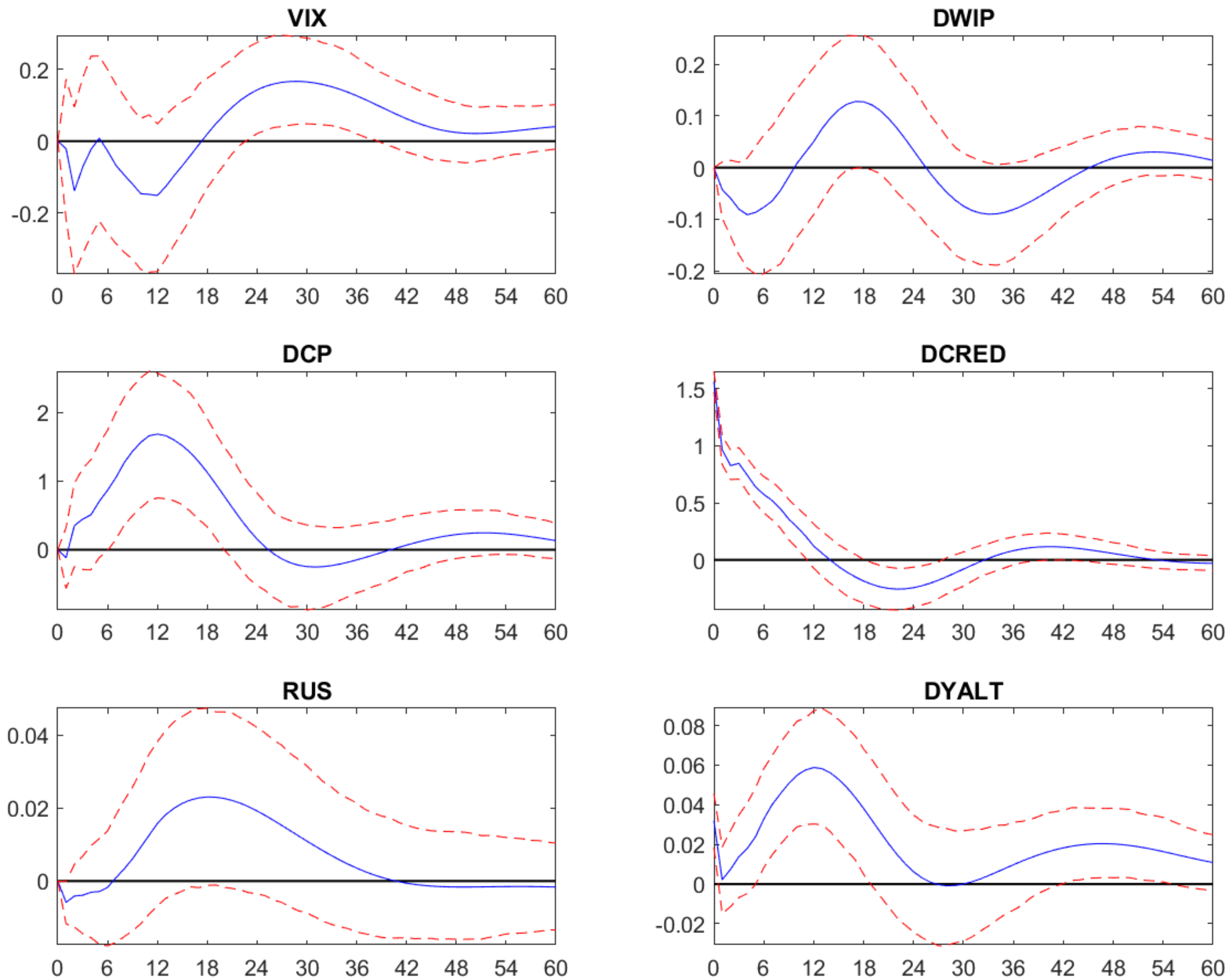
[13]Note that, different from our alternative Chinese growth that tracks 12-month GDP growth, the scale of our Chinese DFM factor has no economic meaning.

Figure 12: Economic responses to a credit impulse shock (2012-2019)



Note: The blue solid lines are the estimated impulse responses to a one standard deviation shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the VIX, commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China (DWIP), the Chinese credit impulse (DCRED) and our Chinese DFM factor (DYFAC). The time period is from January 2012 to December 2019. The time period is from January 2005 to December 2019. The dashed red lines represent +/- one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior.

Figure 13: Economic responses to a credit impulse shock (2009-2019)



Note: The blue solid lines are the estimated impulse responses to a one standard deviation shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the VIX, commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China ($DWIP$), the Chinese credit impulse ($DCRED$) and our alternative Chinese growth measure ($DYALT$). The time period is from January 2009 to December 2019. The dashed red lines represent +/- one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior.

standard deviation increase in the 12-month Chinese credit impulse has a positive impact on Chinese growth. Additionally, we find a large and significant impact on commodity prices with a lag. That said, we find insignificant effects on global manufacturing production. These results highlight an important finding. They suggest that China's economy has been an important driver of commodity prices from the GFC period on. As such, China's massive credit stimulus in 2008 supported not only a strong rebound in China, but also in commodity exporting emerging markets. That said, China's economy moved to a significant driver to the global manufacturing cycle only after the Great Financial Crisis, generating a structural shift in the global economy. This is consistent with the stylized facts in section 3, which documents China's surge in the global footprint.

6.2 Variance Covariance Decomposition

In this section, we quantify China's contribution to the global cycle. Table 1 presents the distribution of the forecast error variance explained by a credit-impulse shock at different horizons—on impact (horizon 0), and 2, 4, 6, 8, 12, and 24 months after the shock. The variance decomposition is presented for the median (50%),and one standard deviation below (16%) and above (84%). We focus here on the contribution of such a shock on the industrial production in the world excluding China and on the global commodity prices. The top panel presents results for the model with the estimated Chinese DFM factor, and the bottom panel presents results for China's alternative growth model. Recall that the difference is that the alternative growth series uses the DFM factor but maps it on China official growth trend.

The top panel in table 1 shows that China's credit-impulse shock explains 15 percent of global industrial production movements after 24 months, and 21 percent of commodity prices. These are large contributions, especially for commodity prices. In a recent paper, Fernández et al. (2020) find that world shocks that affect commodity prices explain more than half of the variance of output growth on average across countries. Our results highlight that China explains the majority of those shocks post-GFC. Finally, we find that the shock to China's credit impulse is transmitted through the Chinese economy as the effects lead the impact on commodity prices and global industrial production.

Turning to the bottom panel in table 1, we consider the distribution of the forecast error variance explained by a credit-impulse shock when we use China's alternative growth series. We find quantitatively similar results for global industrial production and commodity prices. China's credit-impulse shock explains 15 percent of global industrial production movements after 24 months,

Table 1: Distribution of the Forecast Error Variance

Horizon	Global IP ex. China			Commodity Prices			Chinese DFM Factor		
	16%	50%	84%	16%	50%	84%	16%	50%	84%
0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	10.2	17.7
2	0.1	0.4	1.2	0.6	2.2	5.1	3.4	7.1	12.8
4.0	0.2	0.6	1.7	2.1	6.3	12.6	4.1	8.3	15.3
6.0	0.5	1.2	2.9	4.1	10.7	20.4	5.5	11.3	21.2
8	1.0	2.5	5.7	6.0	14.8	27.4	6.9	15.0	27.4
12.0	3.7	8.5	16.3	10.2	21.7	37.8	8.4	19.3	34.8
24.0	7.3	15.3	28.1	9.6	21.0	40.1	7.9	17.1	31.5

Horizon	Global IP ex. China			Commodity Prices			Chinese Alt. GDP		
	16%	50%	84%	16%	50%	84%	16%	50%	84%
0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.9	8.6	15.2
2.0	0.1	0.5	1.5	0.5	2.0	4.7	3.0	6.6	12.1
4.0	0.2	0.7	2.1	1.8	6.0	12.4	3.5	8.0	15.1
6.0	0.5	1.3	3.0	3.9	10.6	19.8	4.1	9.9	19.3
8	1.1	2.6	5.5	6.7	15.1	27.3	4.8	11.7	23.1
12.0	3.6	8.6	15.9	10.5	21.8	38.6	4.5	12.2	25.6
24.0	6.9	15.3	29.8	10.1	22.0	42.1	3.9	9.9	20.4

Note: The table reports the distribution of forecast error variance explained by a credit impulse shock at different horizons - namely at 0, 2, 4, 6, 8, 12, and 24 months after the shock. Variance decomposition presented at the median (50%), and one standard deviation below (16%) and above (84%). Global industrial production (IP) and commodity prices do not react to a credit shock on impact (horizon $h = 0$) by construction.

and 22 percent of commodity prices. Interestingly, the forecast error variance explained by China's alternative GDP series is somewhat smaller, about 10 percent after 24 months, compared to the Chinese DFM factor itself, with 17 percent. This suggests that the DFM factor is more successful in capturing the Chinese cycle than the alternative GDP growth, which may be contaminated by noise from the official GDP trend and from the mapping step itself.

7 Robustness

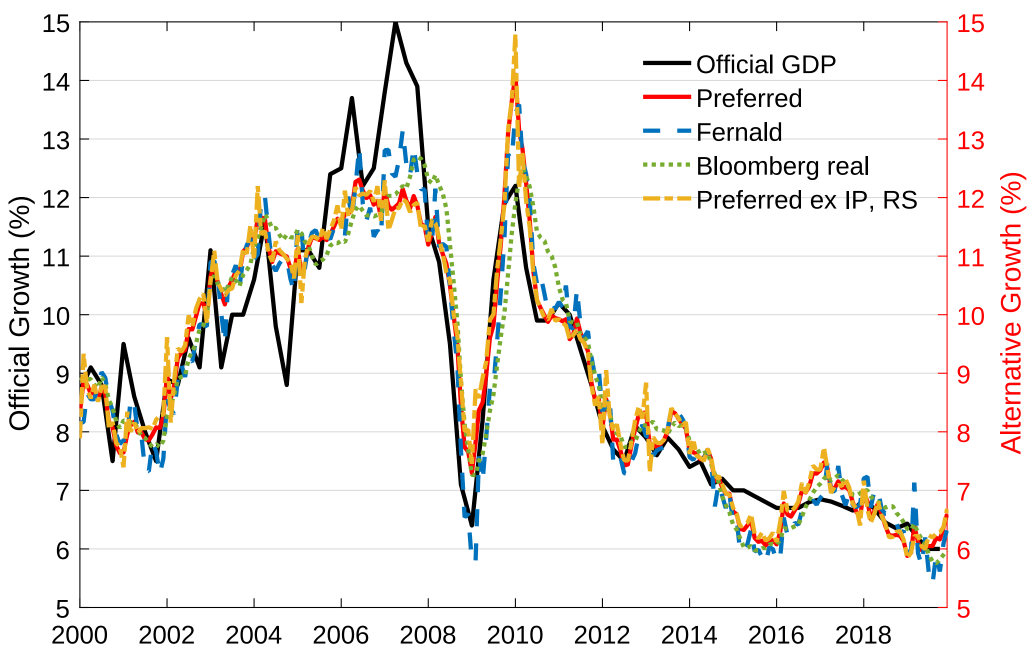
7.1 Alternative growth model specification

In this section we check how sensitive our main result is to different model specifications. We first estimate a dynamic factor model for four additional models. Then we estimate four structural vector autoregressive models using each specification. Finally, we calculate the contribution of an expected shock to China's credit impulse as propagated through the Chinese economy for each model. As such, we can provide an estimated range of China's contribution to the global cycle.

We estimate three additional alternative models to proxy for Chinese growth: (1) Fernald et al. (2020) model, (2) Bloomberg indicator model, and (3) preferred model excluding industrial production and retail sales.[14] We use the same method to estimate our alternative growth measure as we used for our preferred model. We first present results for the different models estimated from 2000 on and then for 2012 on.

Figure 14 presents the model comparisons for the different DFM estimated from 2000 on. Our preferred model highlights that our alternative GDP estimate shows more volatility compared to official GDP in recent years. We find a stronger downturn in the 2015 episode and a stronger upturn in the subsequent stimulus.

Figure 14: Alternative versus Official Growth



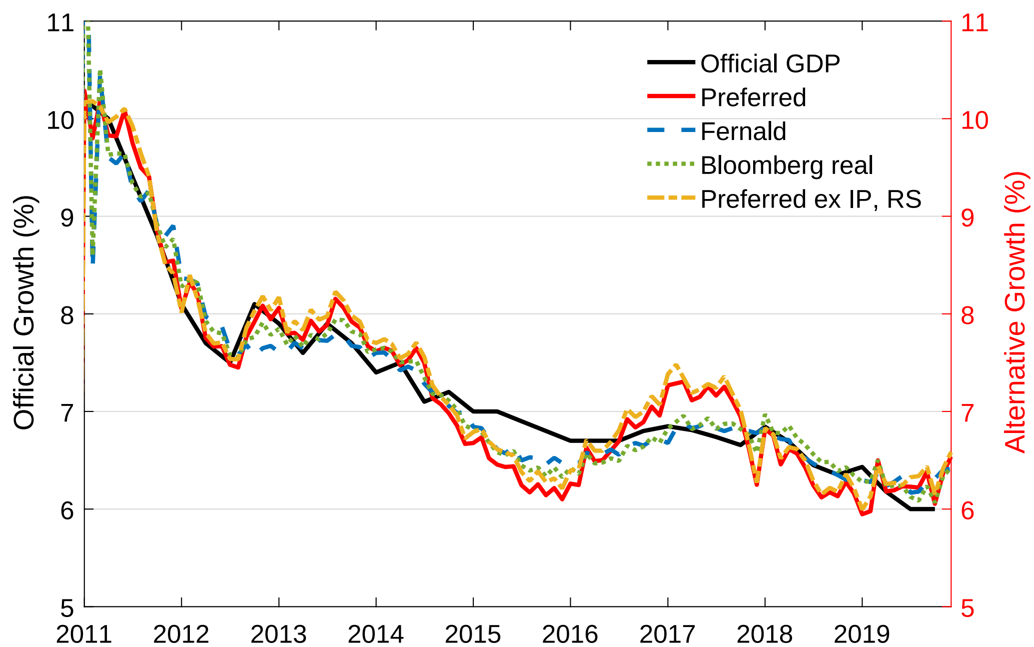
Next, we consider a model where we include the series from Fernald et al. (2020). Similar to our preferred model, the DFM estimated with the series in Fernald et al. (2020) shows a stronger-than-reported downturn in 2015. Then, we consider a model where we include the series from the Bloomberg indicators. Similar to our preferred model and the Fernald et al. (2020) model, the Bloomberg indicator model shows a stronger-than-reported downturn in 2015. It also shows a strong upturn post 2015, as our preferred model also finds. Finally, we consider our preferred model specification without industrial production and retail sales to alleviate concerns these series show similar smoothness as the official GDP series does. We find that the model estimate since 2000 is very similar to all other models.

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

All told, figure 14 highlights that all models estimated from 2000 on show a similar patterns. We find that this similarity is in large part driven by the relative large weight the DFM places on Chinese exports. However, as we documented earlier, China's dependence on exports has declined notably after the GFC. As such, we compare all models when estimated from 2011 on.

Figure 15 presents the model comparisons for the different DFM estimated from 2011 on. Our preferred model shows the same volatility we estimated from 2000 on in recent years. We find a stronger downturn in the 2015 episode and a stronger upturn in the subsequent stimulus. In contrast, the Fernald et al. (2020) model does not show the same volatility as our preferred model. It shows a more muted 2015 downturn and subsequent upturn. Additionally, the model shows that estimated growth has been more or less in line with official growth since 2018. Therefore, it does not show the sharper-than-reported slowdown from the end of 2017 on our preferred model shows. Similar to the Fernald et al. (2020) model, the Bloomberg indicator model is less volatile compared to our preferred model when estimated from 2011.

Figure 15: Model Comparison - Estimated from 2011 to 2019



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

7.2 VAR Specifications

In this subsection, we explore different VAR specifications. We first estimate a monthly VAR with the same variables as our main specification, but use Chinese imports instead of our estimated alternative growth measure. Similar to our main model, we identify a credit impulse shock through a recursive Cholesky decomposition in a block exogeneity structure, where the credit impulse is ordered first after all the global and foreign indicators. As such, an exogenous credit impulse shock can contemporaneously affect Chinese imports, but its effects on the rest of the world are only observed with one-month lag. The ordering of the variables is defined as

$$\mathbf{y}_t = \begin{bmatrix} VIX_t \\ DCP_t \\ RUS_t \\ DWIP_t \\ DCRED_t \\ DIMP_t \end{bmatrix}, \tag{8}$$

where $DIMP_t$ are total Chinese imports. We construct this aggregate as total foreign reported exports to China and Hong Kong following (Fernald et al., 2020). We estimate our model from 2012 to 2019.

The impulse response functions are show in figure 16. We find that a one standard deviation shock to China's credit impulse significantly increases Chinese imports on impact, with positive effects for about 12 months. This is similar to the earlier results for China's alternative growth estimate. What this result highlights, however, is more direct evidence of the transmission channel. Indeed, the impulse response functions show that China's credit policies constitute an important driver of Chinese global demand. With respect to the other variables, we find that global industrial production excluding China also increases in the medium run, but with a lag compared to China's increased global demand. This path indicates that the positive effects of the credit impulse are transmitted to the rest of the world and are driven by a boost to global manufacturing through increased Chinese demand.

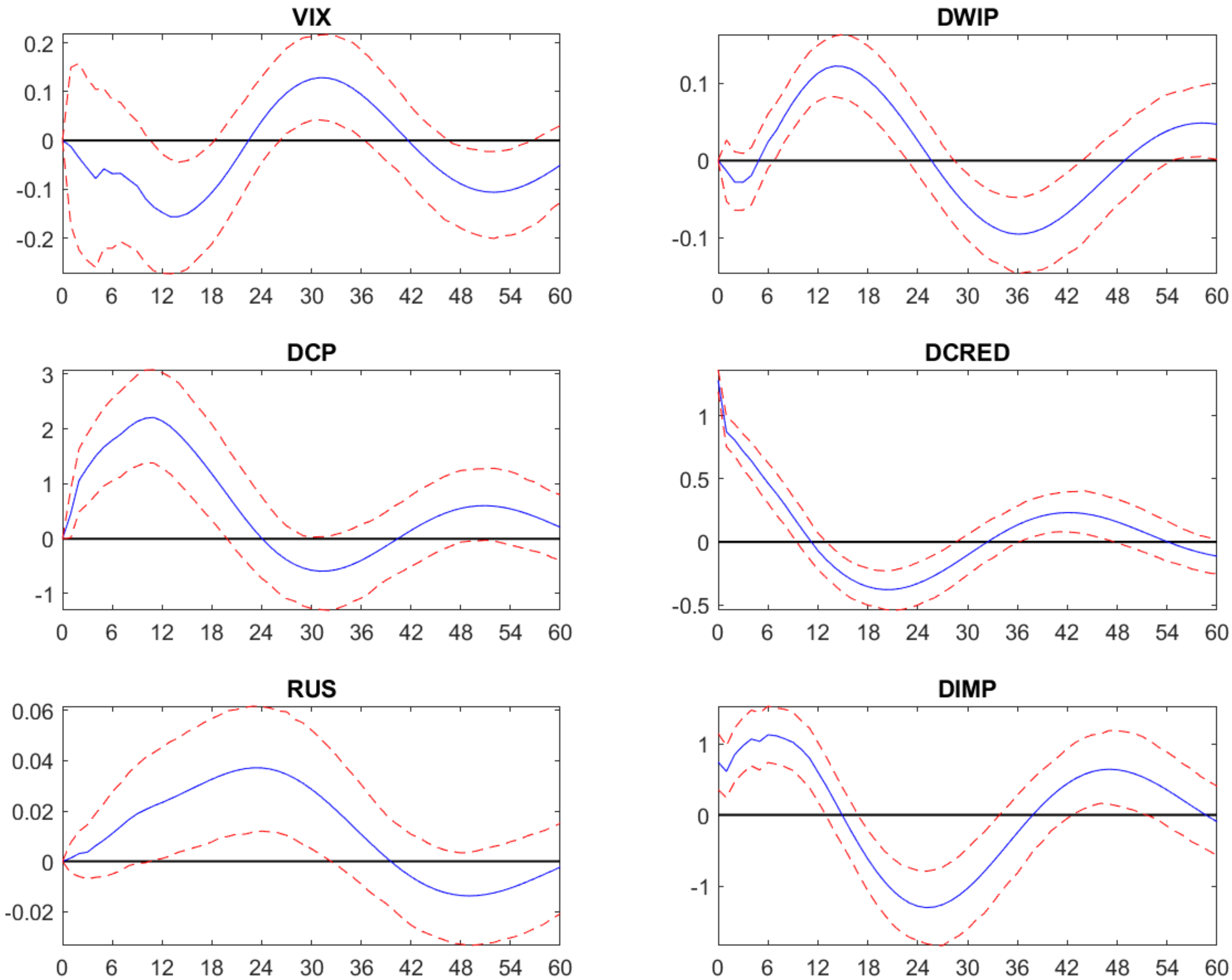
Next, we estimate a VAR where we substitute China's alternative growth measure with China's industrial production. Similar to previous specifications, the ordering of the variables is defined as

$$\mathbf{y}_t = \begin{bmatrix} VIX_t \\ DCP_t \\ RUS_t \\ DWIP_t \\ DCRED_t \\ DCHIP_t \end{bmatrix}, \tag{9}$$

where $DCHIP_t$ is Chinese industrial production. We estimate our model from 2012 to 2019.

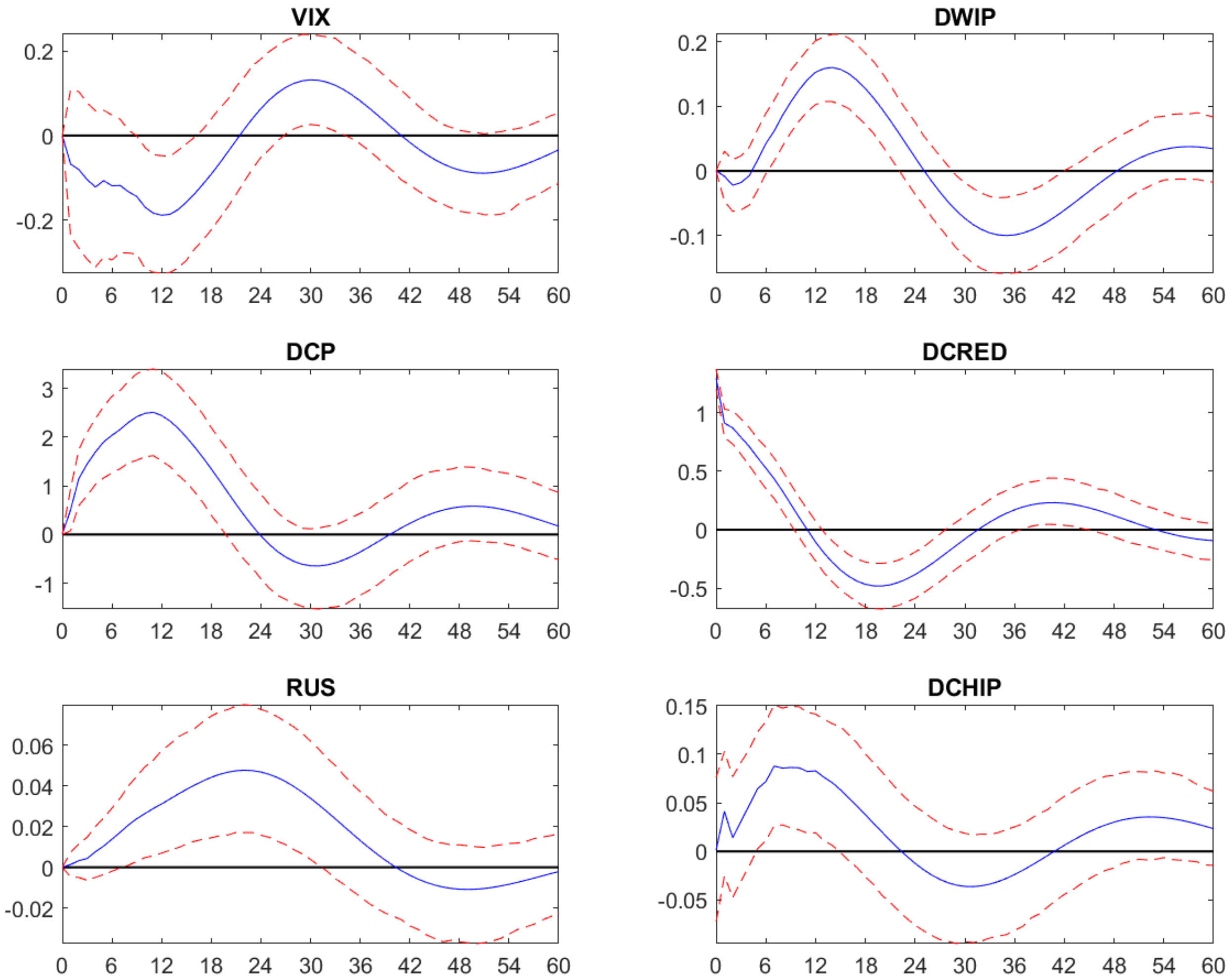
The impulse response functions following a one standard deviation shock to China's credit impulse are show in figure 17. Interestingly, we find a more muted effect on Chinese industrial production. Additionally, the positive effects are less pronounced and less significant compared to our alternative growth estimate. This result suggests that China's industrial production is less responsive to China's credit policies. However, given that China's industrial production has also experienced a notable decline in volatility, similar to official GDP, these results could suggest that the official data might mask the actual impact on industrial production. Hence, these results seem to confirm underscore the importance of using a wide set of variables to track the underlying state of the Chinese economy as we proposed with our alternative growth estimate.

Figure 16: Economic responses to a 1 stdev. credit impulse shock (2012-2019)



Note: The blue solid lines are the estimated impulse responses to a one standard deviation shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the VIX, commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China ($DWIP$), the Chinese credit impulse ($DCRED$) and total Chinese imports ($DIMP$). The time period is from January 2012 to December 2019. The dashed red lines represent +/- one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior.

Figure 17: Economic responses to a 1 stdev. credit impulse shock (2012-2019)



Note: The blue solid lines are the estimated impulse responses to a one standard deviation shock to China's credit impulse and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR composed of the following: the VIX, commodity price index (DCP), the 3-month U.S. Treasury bill (RUS), global industrial production excluding China (DWIP), the Chinese credit impulse (DCRED) and Chinese industrial production (DCHIP). The time period is from January 2012 to December 2019. The dashed red lines represent +/- one standard deviation confidence bands of the credit impulse shock obtained with 1,000 draws from the posterior.

8 Conclusion

China's economy has grown rapidly over the past decades and has transformed the global landscape with it. Whereas China represented a small fraction of global GDP and global trade in the 1990s, it now accounts for 16 percent of world GDP and more than 30 percent of global growth. Yet, China's role as a major engine of global growth has been largely unexplored, potentially driven by the observation that its official GDP is seemingly uncorrelated with the global cycle. In this paper, we quantify the role of China's economy in driving the global cycle. Specifically, we estimate the impact of China's credit policies on global commodity prices and economic activity. To do so, we first construct China's credit impulse, which aggregates different credit measures the Chinese authorities employ. Next, we construct an alternative growth series for China that better captures the volatility of underlying Chinese economic activity. Finally, we estimate a Structural Vector Autoregressive Model (VAR) to estimate the impact of movements in Chinese economic activity induced by China's domestic credit stimulus or tightening on economic activity in the rest of the world. Our results show that China's credit policies since the Great Financial Crisis have played an important role in supporting economic growth in China and also globally. We find that shocks to China's credit policies explain 15 percent of the global industrial production movements and 21 percent of global commodity price movements over two years, which highlights China's importance in contributing to the global cycle.

References

Aruoba, S. Borağan, Francis X. Diebold, and Chiara Scotti, "Real-Time Measurement of Business Conditions," *Journal of Business and Economic Statistics*, 2009, *27* (4), 417–427.

_ , _ , Ayhan Kose, and Marco Terrones, "Globalization, the Business Cycle, and Macroeconomic Monitoring," *NBER International Seminar on Macroeconomics 2010*, 2011, pp. 245–286.

Bańbura, Marta and Michele Modugno, "Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data," *Journal of Applied Econometrics*, 2014, *29* (1), 133–160.

Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin, "Large Bayesian vector auto regressions," *Journal of Applied Econometrics*, 2010, *25(1)*, 71–92.

Barhoumi, Karim, Olivier Darné, and Laurent Ferrara, "Are disaggregate data useful for factor analysis in forecasting French GDP?," *Journal of Forecasting*, 2010, *29* (1-2), 132–144.

Baxter, M. and M.A. Kouparitsas, "Determinants of Business Cycle Comovement: A Robust Analysis," *Journal of Monetary Economics*, 2005, *52*, 113–157.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo, "The Economic Effects of Trade Policy Uncertainty," *Journal of Monetary Economics*, 2019, *Forthcoming.*

Calderon, Cesar, Alberto Chong, and Ernesto Stein, "Trade intensity and business cycle synchronization: Are developing countries any different?," *Journal of International Economics*, 2007, *71*, 2–21.

Camacho, Maximo and Gabriel Perez-Quiros, "Introducing the euro-sting: Short-term indicator of euro area growth," *Journal of Applied Econometrics*, 2010, *25* (4), 663–694.

Cascaldi-Garcia, Danilo, Thiago Ferreira, Domenico Giannone, and Michele Modugno, "Back to the Present: Learning about th Euro Area through a Now-casting Model ," Mimeo 2020.

Chen, Wei, Xilu Chen, Chang-Tai Hsieh, and Zheng Song, "A Forensic Examination of China's National Accounts," *Brookings Papers in Economic Activity*, 2019, *Spring.*

Clark, Hunter L., Maxim Pinkovskiy, and Xavier Sala-i-Martin, "China's GDP growth may be understated," *China Economic Review*, December 2018.

Crucini, Mario J., Ayhan Kose, and Christopher Otrok, "What Are the Driving Forces of International Business Cycles?," *Review of Economic Dynamics*, 2011, *14* (1), 156–175.

de Soyres, François and Alexandre Gaillard, "Value Added and Productivity Linkages Across Countries," *International Finance Discussion Papers 1266*, November 2019.

_ and _ , "Global Trade and GDP Co-movement," *Working paper*, 2020.

Doz, C., D. Giannone, and L. Reichlin, "A quasi-maximum likelihood approach for large, approximate dynamic factor models," *Review of Economics and Statistics*, 2006, *94* (4), 1014–1024.

Duval, Romain, Nan Li, Richa Saraf, and Dulani Seneviratne, "Value-added trade and business cycle synchronization," *Journal of International Economics*, 2015, *99*, 251–262.

D'Agostino, Antonello, Michele Modugno, and Chiara Osbat, "A Global Trade Model for the Euro Area," *International Journal of Central Banking*, December 2017, *13* (4), 1–34.

Fernald, John G., Eric Hsu, and Mark M. Spiegel, "Is China Fudging Its GDP Figures? Evidence from Trading Partner Data," *China Economic Review*, 2020, *Forthcoming.*

Fernández, Andrés, Stephanie Schmitt-Grohé, and Martín Uribe, "Does the Commodity Super Cycle Matter?," NBER Working Papers 27589, National Bureau of Economic Research, Inc Jul 2020.

Giannone, Domenico, Lucrezia Reichlin, and David Small, "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 2008, *55* (5), 665–676.

_ , Silvia Miranda-Agrippino, and Michele Modugno, "Nowcasting China Real GDP," Technical Report, Mimeo New York, NY 2013.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil, "Measuring Economic Growth from Outer Space," *American Economic Review*, April 2012, *102* (2), 994–1028.

Huo, Zhen, Andrei A. Levchenko, and Nitya Pandalai-Nayar, "International Comovement in the Global Production Network," *NBER Working Paper 25978*, 2020.

IMF, WEO, "World Economic Outlook: Global Manufacturing Downturn, Rising Trade Barriers," *World Economic Outlook - IMF*, October 2019.

Johnson, Robert C., "Trade in Intermediate Inputs and Business Cycle Comovement," *American Economic Journal: Macroeconomics*, 2014, *6*, 39–83.

Kalemli-Özcan, Şebnem, Elias Papaioannou, and José-Luis Peydró, "Financial regulation, financial globalization, and the synchronization of economic activity," *Journal of Finance*, June 2013, *68* (3), 1179–1228.

Kose, M. Ayhan and Kei-Mu Yi, "International Trade and Business Cycles: Is Vertical Specialization the Missing Link?," *American Economic Review*, 2001, *91*, 371–375.

_ **and** _ , "Can the standard international business cycle model explain the relation between trade and comovement?," *Journal of International Economics*, 2006, *68*, 267–295.

Liao, Wei and Ana Maria Santacreu, "The trade comovement puzzle and the margins of international trade," *Journal of International Economics*, 2015, *96*, 266–288.

Litterman, Robert B., "Forecasting with Bayesian vector autoregressions: five years of experience," *Journal of Business & Economic Statistics*, 1986, *4(1)*, 25–38.

Luciani, Matteo and Lorenzo Ricci, "Nowcasting Norway," *International Journal of Central Banking*, December 2014, *10* (4), 215–248.

Mariano, Roberto S. and Yasutomo Murasawa, "A new coincident index of business cycles based on monthly and quarterly series," *Journal of Applied Econometrics*, 2003, *18* (4), 427–443.

Matheson, Troy D, "An analysis of the informational content of New Zealand data releases: the importance of business opinion surveys," *Economic Modelling*, 2010, *27* (1), 304–314.

Modugno, Michele, "Now-casting inflation using high frequency data," *International Journal of Forecasting*, 2013, *29* (4), 664–675.

Monnet, Eric and Damien Puy, "One Ring to Rule Them All? New Evidence on World Cycles," *IMF Working Paper WP/19/202*, September 2019.

Morris, Stephen D. and Junjie Zhang, "Validating China's Output Data Using Satellite Observations," *Macroeconomic Dynamics*, 2019, *forthcoming.*

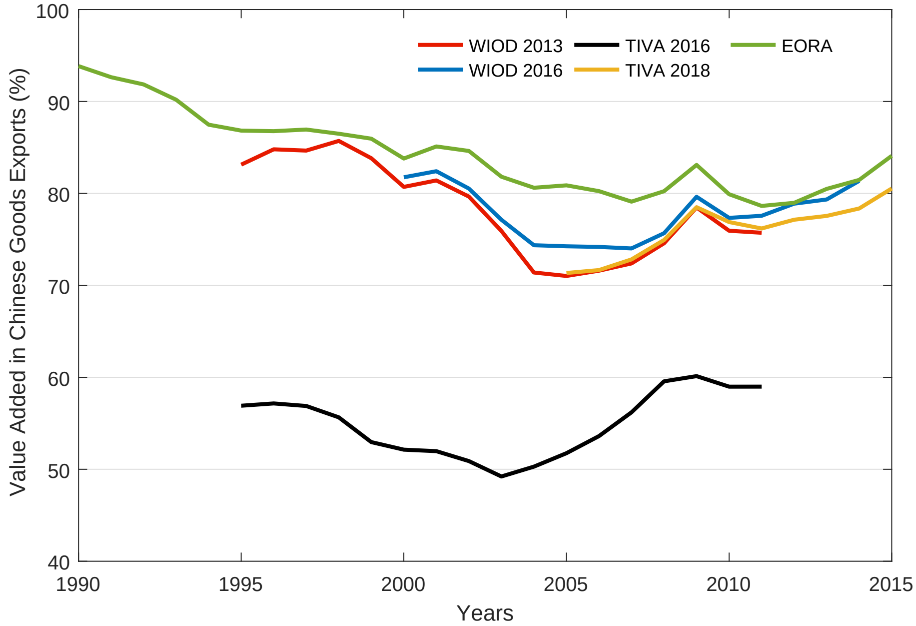
Nakamura, Emi, Jón Steinsson, and Miao Liu, "Are Chinese Growth and Inflation Too Smooth? Evidence from Engel Curves," *American Economic Journal: Macroeconomics*, July 2016, *8* (3), 113–44.

Yiu, Matthew S and Kenneth K Chow, "Nowcasting Chinese GDP: information content of economic and financial data," *China Economic Journal*, 2010, *3* (3), 223–240.

A Appendix

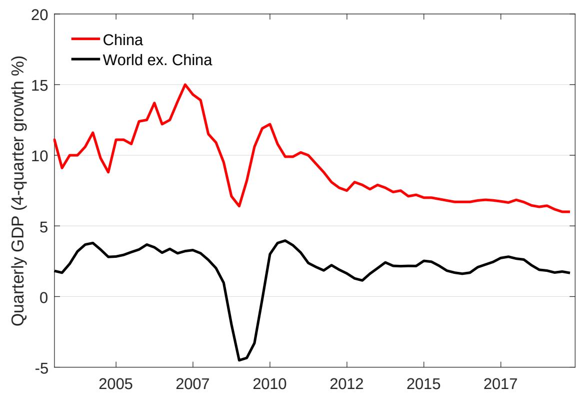
A.1 Value Added in Chinese Exports - Different sources

Figure A.1: Value Added in Chinese Exports - Different sources (%)

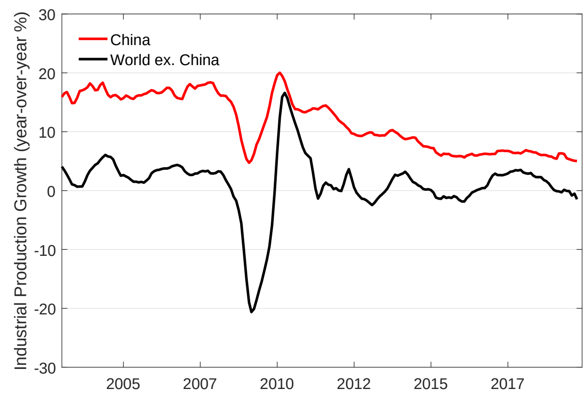


A.2 China's co-movement with the global cycle

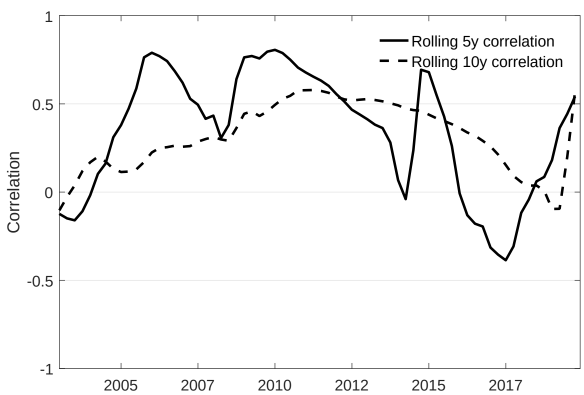
Figure A.2: China's economy and the global cycle



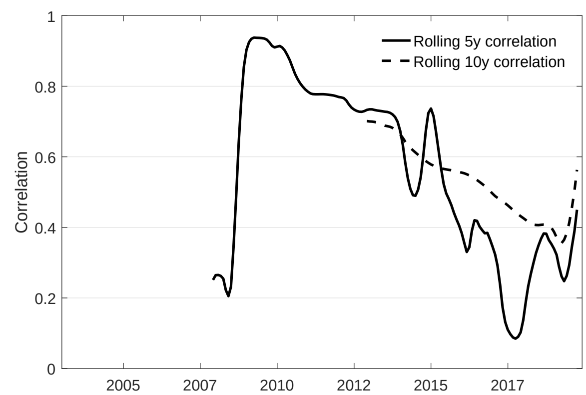
(a) Real GDP growth (%)



(b) Industrial production growth (%)



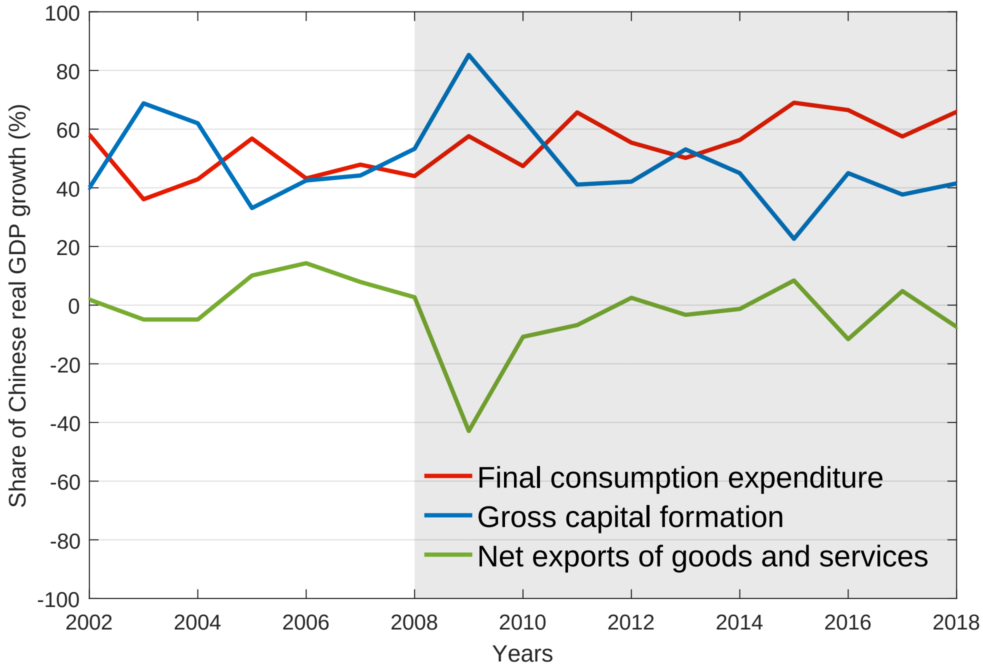
(c) Real GDP growth correlation



(d) Industrial production growth correlation

A.3 Decomposition of China's official GDP - Demand side components

Figure A.3: China's demand side shares of real GDP growth (%)



A.4 Model Specification and Comparison

Figure A.4 presents our preferred model alternative Chinese growth estimate and world excluding China GDP growth.

Figure A.4: Alternative growth versus the global cycle

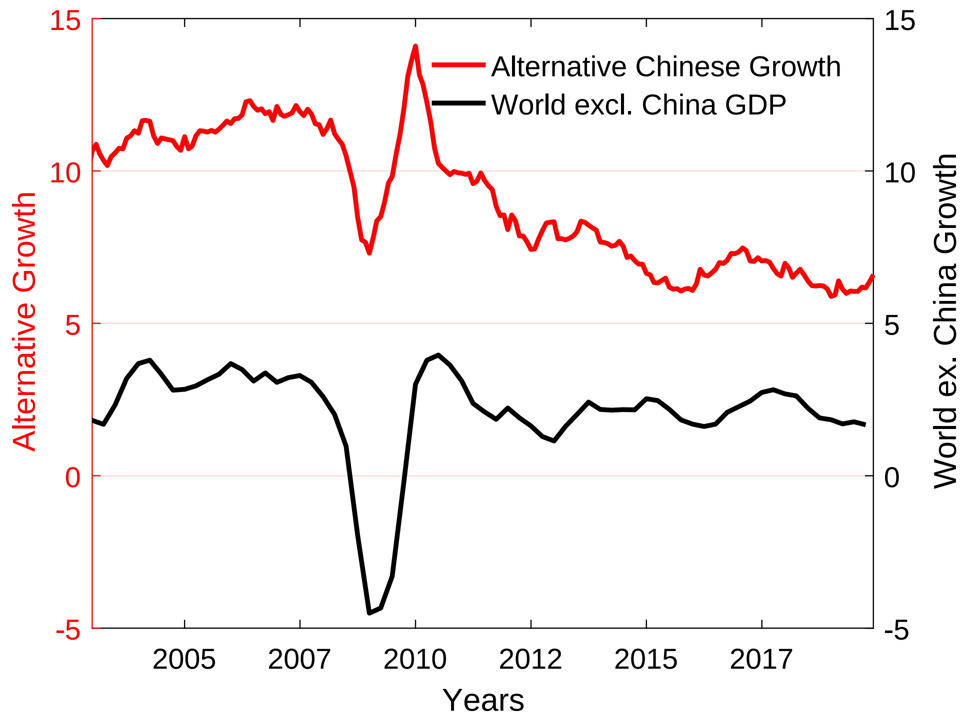


Table A.1: Model Specifications

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