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# China's Economic Slowdown and International Inflation Dynamics

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## Abstract

I examine the impact of the Chinese economic slowdown that started after the Great Recession on global inflation dynamics. To this end, I fit a high-dimensional data set comprising macroeconomic indicators of 41 countries to a structural factor-augmented vector autoregressive model. My main findings are: (i) Business cycle shocks and especially demand shocks in China significantly spill over to inflation rates in the US, Europe, Asia, and Oceania and are transmitted by global oil, commodity, and steel prices. (ii) The decline in Chinese growth rates can be attributed to a combination of negative aggregate demand and supply shocks. (iii) Historical decompositions indicate that after 2014, these shocks lowered PPI inflation rates outside of China by up to 0.3 percentage points per quarter, resulting in a cumulative effect on the PPI of six percent. Hence, they markedly contributed to the decline in global inflation rates and hampered the recent upward trend. (iv) The Chinese influence is also reflected in interest rates outside of China by a reduction of yields at the current edge.

*Keywords:* China's Economic Slowdown, Global inflation, Spillovers, FAVAR

*JEL classification:* E31, E32, E43

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## 1. Introduction

It is widely known that inflation rates have been globally declining after the Great Recession, reaching values close to zero. Figure 1 shows that from 2011 to 2015, they fell in all economic areas of the world and increased again only recently. In the US, for example, CPI inflation fell from 3.2 percent in 2011 to 0.1 percent in 2015.

While this decline can be partly explained by domestic factors (Ciccarelli et al., 2017 and Bobeica et al., 2017), there is also evidence pointing to influence from the emerging economies, especially from China. Aastveit et al. (2015), for example, show that the demand from emerging economies has become twice as important as the demand from developed countries in accounting for the fluctuations in oil prices. Besides, Eickmeier and Kühnlenz (2016) find that aggregate demand shocks from China account for eleven percent in the variance of crude oil prices and five percent in the variance of US consumer prices.

In light of these findings, the question arises which role China played for global inflation rates during the last decade, notably since the Chinese business cycle experienced a marked slowdown after the Great Recession. Figure 2 illustrates this slowdown in terms of Chinese GDP growth and inflation. After very high GDP growth rates of up to 13.1 percent in the period 2001-2007, the Great Recession kicked in and reduced GDP growth to 8.7 percent in 2008. The subsequent, weak recovery in 2009 and 2010 is followed by repeatedly falling growth rates, from 9.3 percent in 2010 to 4.5 percent in 2017<sup>1</sup>. China's inflation rate lags behind output,

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<sup>1</sup>The GDP growth rate published by the World Bank slightly differs from that of Chang et al. (2016) in 2016 and 2017. However, I show in section 5.4 that the choice between the two indicators does not play a role in my conclusions.

dropping to -0.2 percent only in 2009. Afterwards, it increased again to 7.8 percent in 2011 and then continuously fell to 0.1 percent in 2015. In 2016, it increased once more and reached 4.0 percent in 2017.

As a result, we observe a substantial and persistent decline in Chinese GDP growth and inflation rates after 2011 and a trend reversal of inflation rates in 2016. Furthermore, China's business cycle was significantly correlated with inflation rates worldwide during this period.

The aim of this work is to quantify the Chinese contribution to the decline in global inflation rates. To the best of my knowledge, this issue has not been examined in the literature yet. Dizioli et al. (2016) only consider the impact of the Chinese business cycle on real activity in five major Asian economies. They find that the Chinese influence is larger in economies which are commodity exporters and have strong trade links with China, namely Malaysia, Singapore, and Thailand. Metelli and Natoli (2017) investigate the effects on inflation in the Euro Area and the United States using the NiGEM multi-country model. They show that China's economic downturn has led to a significant disinflation in both regions. However, these results are based on different slowdown scenarios imposed on a theoretical model and not on the data.

To empirically identify the Chinese business cycle, I use the factor-augmented vector autoregressive model (FAVAR) suggested by Bernanke et al. (2005). The FAVAR allows flexible economic modeling while keeping dimensionality manageable. I proceed as follows: First, I estimate a set of factors from a large data set of 749 national and international macroeconomic time series covering nominal and real indicators of 41 major economies, including all OECD countries. These factors are added to a classical VAR model of the Chinese GDP growth rate and

the Chinese inflation rate serving as business cycle controls. Subsequently, I identify aggregate supply and demand shocks in China by imposing sign restrictions on the impulse response functions of the domestic indicators. To examine the international propagation of these shocks, I compute impulse response functions of global price indicators and national price indicators in the US, Europe, Asia, and Oceania. Using historical decompositions, I additionally assess their role during the period of China's cyclical downturn. I present the Chinese structural shock series over the course of the last decade and quantify their impact on inflation indicators worldwide. Finally, I examine the implications for long-term interest rates in the tradition of the Fisher effect.

The results show that business cycle shocks and especially aggregate demand shocks in China significantly spill over to global oil, commodity, and steel prices and national inflation rates in the US, Europe, Asia, and Oceania. The international effects are most substantial in the US and generally translate more in terms of producer prices than consumer prices. The decline in Chinese growth rates after the Great Recession can be attributed to a combination of adverse aggregate demand and supply shocks. From 2014 onwards, these shocks lowered CPI inflation rates outside of China by up to 0.1 percentage points and PPI inflation rates by up to 0.3 percentage points per quarter. They cumulatively reduced oil prices by twelve percent and foreign national PPIS by up to six percent. In accordance with the Fisher effect and monetary policy rules, the shocks are also reflected in interest rates and thus financial indicators outside of China. As a result, the Chinese economic slowdown markedly contributed to the global decline in inflation and interest rates and hampered the recent upward trend.

The rest of the paper is organized as follows: In sections 2 and 3, I present the

FAVAR framework and details on the data. In section 4, I describe the identification and estimation approach. In section 5, I discuss the results of an impulse response analysis, the series of structural shocks, historical decompositions, and extensive robustness checks. Section 6 concludes.

## 2. Factor-augmented vector autoregressive model

To assess the impact of Chinese business cycle shocks on global inflation dynamics, I employ a time series vector  $X_t$  comprising a large number of macroeconomic indicators and countries. The large cross-section has the clear advantage that it allows analyzing different world regions and inflation categories and includes lots of information on global business cycle dynamics. However, the number of time observations of macroeconomic time series is typically small, hence I cannot include all series in a standard VAR jointly with Chinese indicators. Instead, I estimate a two-variable VAR for the Chinese economy that I augment by a latent but estimable common component of the series in  $X_t$ . Here I assume that macroeconomic indicators are strongly driven by global and regional business cycle fluctuations and therefore can be reduced to a handful of common factors. By including these factors in the VAR I keep the model parsimonious and, at the same time, I control for international business cycle movements. This approach goes back to Bernanke et al. (2005) who augment a VAR of the US economy by international factors to study the effects of monetary policy shocks on real variables.

I start with a classical structural VAR:

$$A_0 F_t = \sum_{i=1}^p A_i F_{t-i} + \varepsilon_t \quad (1)$$

that can be transformed into the reduced form

$$F_t = \sum_{i=1}^p B_i F_{t-i} + u_t \quad (2)$$

where  $B_i = A_0^{-1} A_i$ ,  $i = 1, \dots, p$ , and  $u_t = A_0^{-1} \varepsilon_t$ .  $F_t = [H_t', \Delta cgdpt_t, \Delta cdefl_t]'$  is  $k \times 1$ -dimensional and consists of  $r$  (latent) international factors  $H_t = [H_{1,t}, \dots, H_{r,t}]'$ , the Chinese GDP growth rate ( $\Delta cgdpt_t$ ), and the logarithmic difference of the Chinese GDP deflator ( $\Delta cdefl_t$ ). As usual, it holds for the structural shocks  $\varepsilon_t$  and the reduced-form shocks  $u_t$  that  $E(u_t) = E(\varepsilon_t) = 0$ ,  $E(u_t u_t') = \Sigma$  and  $E(\varepsilon_t \varepsilon_t') = I_k$ . The structural shocks  $\varepsilon_t$  are identified by imposing sign restrictions on the reduced-form residuals  $u_t$  (see, e.g., Faust, 1998; Canova and De Nicolò, 2003; Peersman, 2005; Uhlig, 2005). More details on the identification and estimation of  $H_t$  and  $\varepsilon_t$  are described in section 4.

The relationship between  $F_t$  and  $X_t$  follows an approximate factor model along the lines of Bai and Ng (2002) and Stock and Watson (2002):

$$X_t = \Lambda F_t + \Xi_t \quad (3)$$

$\Lambda$  denotes the  $n \times k$ -dimensional loading matrix of the factors  $F_t = [f_{1t}, \dots, f_{kt}]'$  and  $\Xi_t = [\xi_{1,t}, \dots, \xi_{N,t}]'$  is the vector of idiosyncratic components. The  $\xi_{i,t}$ 's are orthogonal to the factors  $F_t$  but are allowed to be weakly correlated between each other and over time in the tradition of Chamberlain and Rothschild (1983).

### 3. Data and detrending

The data vector  $X_t$  comprises  $n = 749$  national macroeconomic time series of 41 countries, namely all OECD countries plus Brazil, Indonesia, India, Russia, and South Africa. For every country I include, if available, GDP, investment, consump-

tion, exports, imports, bilateral exports/imports to/from China, consumer prices, producer prices, the GDP deflator, a broad monetary aggregate M3, overnight interest rates, 3-month and 10-year rates, wages, unit labor costs, real effective exchange rates, employment, and unemployment rates. I also include the following international series: oil prices, fuel prices, steel prices, commodity prices (excluding fuels), manufacturing prices, stock market returns and their variance, inflation variance, world GDP, world industrial production, trade volumes, and the composite OECD leading indicator. The series are either taken from the OECD databases or national statistics offices.

The Chinese indicators are taken from Chang et al. (2016), who construct a standard set of macroeconomic time series comparable to those commonly used in the macroeconomic literature on Western economies. Their main data source is the CEIC's China Premium Database, which compiles China's official macroeconomic time series<sup>2</sup>.

The series are at quarterly frequency and span the period 2000Q1-2017Q4, resulting in  $T = 72$  observations. All of them except unemployment rates, interest rates, real effective exchange rates, and variances are stationarized by taking logarithmic first differences. To prevent my results from being driven by outliers, I follow Carstensen and Salzmänn (2017) and Stock and Watson (2005) in trimming any observation that is further than five times the interquartile range away from its median to the respective threshold.

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<sup>2</sup>In the baseline specification of the FAVAR, the Chinese economy is represented by the (mean-adjusted) GDP growth rate and the (mean-adjusted) inflation rate. To account for the possibility that these rates do not fluctuate around a constant mean but, e.g. exhibit a secular productivity trend, I check in section 5.4 if detrending them with the local-level filter suggested by Stock and Watson (2005) alters my results. Since this is not the case I refrain from using the filter in the baseline setup.



Although the sample covers the Great Recession, I assume a constant volatility regime in my model. I base parts of my conclusions on historical decompositions, which are a function of both the variance matrix of the structural shocks  $E(\varepsilon_t \varepsilon_t')$ , and the VAR coefficient matrices  $B_i$ . On the one hand, shifts in the relative variance of two structural shocks change their relative importance. On the other hand, Carstensen and Salzmann (2017) found only mild heteroskedasticity in a factor structural VAR of the G20 countries over the sample period 1991-2014. Since relaxing the assumption of a constant volatility regime did not change their results, I conclude that heteroskedasticity is not a significant issue in my model, too.

#### 4. Identification and Estimation

The first step of estimating the FAVAR involves finding  $H_t$ . Extracting principal components of  $X_t$  would be the standard practice here but might be problematic if  $H_t$  is supposed to represent the international non-Chinese business cycle in the FAVAR system (1)-(3). It is quite likely that the first principal components of  $X_t$  do not only mirror the international business cycle but also contain a share associated with the Chinese economy. In a FAVAR that comprises Chinese GDP growth and inflation and the principal components of  $X_t$  it is therefore hard to distinguish Chinese shocks from international ones.

To account for this issue, I apply a “cleaning” procedure proposed by Bernanke et al. (2005) that isolates the international business cycle from the Chinese observables  $\Delta cdefl_t$  and  $\Delta cgdpt_t$ . The cleaning is executed as follows: First, I extract the first principal components of  $X_t$  and take them as a first estimate for the unobserved factors  $H_t$ , defined as  $\hat{H}_t^0$ . The number of principal components is

determined by the *IC2* criterion proposed by Bai and Ng (2002) and accordingly set to  $r = 5$  (see Table 1). The share in the variance of  $X_t$  explained by these five principal components amounts to 79 percent. In the next step, I model  $\hat{H}_t^0$  as a linear combination of Chinese and non-Chinese business cycle components:

$$\hat{H}_t^0 = b_{H^*} \hat{H}^* + b_{cdefl} \Delta cdefl_t + b_{cgdp} \Delta cgdp_t \quad (4)$$

where  $\hat{H}^*$  represents the non-Chinese component. If this linear combination and especially  $\hat{H}^*$  was known, the Chinese share could be removed from  $\hat{H}_t^0$  by subtracting  $b_{cdefl} \Delta cdefl_t + b_{cgdp} \Delta cgdp_t$  from it. Since this is not the case, I need to find  $\hat{H}^*$  to estimate equation (4) in a multiple regression. One way to obtain  $\hat{H}^*$  is to extract principal components from the subset of  $X_t$  of slow-moving variables<sup>3</sup>, which by assumption are predetermined concerning  $\Delta cdefl_t$  and  $\Delta cgdp_t$ . I follow Bernanke et al. (2005) in assuming that real quantities and composite price indices are slow-moving. The remaining subset of fast-moving variables accordingly consists of the monetary aggregate M3, interest rates, stock market variables, exchange rates, and prices of oil, steel, and commodities. Hence, real economic indicators and composite price indices outside of China need at least one quarter to react to Chinese business cycle shocks, while financial variables and commodity prices react instantaneously<sup>4</sup>. To obtain the “cleaned” estimate  $\hat{H}_t^1$ , I estimate equation (4) by ordinary least squares and subtract  $b_{cdefl} \Delta cdefl_t + b_{cgdp} \Delta cgdp_t$

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<sup>3</sup>The number of slow-moving variables amounts to 67 percent of all variables in  $X_t$ . I again rely on the *IC2* criterion of Bai and Ng (2002) in choosing the number of factors, which suggests four factors.

<sup>4</sup>Although these assumptions are widely accepted in the literature (see, e.g., Bernanke et al., 2005 and Cesa-Bianchi, 2013), I tested different classifications of the variables as “slow-moving” and “fast-moving” and checked the robustness of my results. As it turns out, the results are not significantly affected and my conclusions remain intact.

from  $\hat{H}_t^0$ .

Next, I turn to estimating the actual FAVAR system (1)-(3). I estimate the loadings  $\Lambda$  by regressing  $X_t$  on  $\hat{F}_t = [\hat{H}_t^1, \Delta cgdpt, \Delta cdeflt]'$ . This procedure is valid since the principal components of  $X_t$  estimate the unobserved common component of  $X_t$   $n$ -consistently, hence I do not face the problem of generated regressors. To examine domestic effects of Chinese business cycle shocks, I also include key indicators of the Chinese economy as dependent variables in this regression. The results are presented in section 5.1. Subsequently, I estimate the VAR system (1)-(2) by ordinary least squares, which gives me the reduced form residuals  $u_t$  and the residual covariance matrix  $\Sigma$ . I follow Eickmeier (2010) in setting the VAR lag length  $p = 2^5$ .

To identify the structural shocks  $\varepsilon_t$ , I impose two theory-based sign restrictions on the reduced-form shocks  $u_t$ . First, I orthogonalize them by the inverse of the Cholesky factor of  $\Sigma$ . Here I order the Chinese variables behind  $\hat{H}_t^1$  such that they react contemporaneously to all variables, whereas  $\hat{H}_t^1$  reacts to the Chinese shocks only after one quarter. This ordering is consistent with the assumptions on the slow-moving variables in  $X_t$  in the cleaning equation (4). Since the fast-moving variables are assumed to react instantaneously to Chinese shocks, I checked if ordering the Chinese variables before  $\hat{H}_t^1$  alters my results. It turned out, however, that this reordering does not play a significant role. Further details are described in section 5.4. Second, I rotate the two orthogonalized Chinese shocks to identify an aggregate supply (AS) shock and an aggregate demand (AD) shock in China.

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<sup>5</sup>Whereas the BIC and the HQ point to  $p = 1$  the AIC suggests  $p = 3$ . To check if my results hinge on a higher lag order I re-estimate the model with  $p = 3$ . It turns out, however, that my conclusions are not affected. Details are presented in section 5.4.

The identification of the shocks rests upon sign restrictions imposed on the impulse response profile of the Chinese indicators. The restriction scheme is the following: the AD shock is defined as a shock that drives Chinese GDP growth and inflation in the same direction. The AS shock, by contrast, is a shock that drives the same variables in opposite directions<sup>6</sup>. These assumptions are consistent with a large number of theoretical models such as the IS-LM model or New-Keynesian models à la Smets and Wouters (2003) and have often been applied in the empirical literature (e.g., Peersman, 2005 and Eickmeier, 2010).

I implement the restrictions by means of a  $k$ -dimensional identity matrix  $R$  whose lower-right  $2 \times 2$  submatrix is replaced by a Given's rotation matrix. Hence,  $R$  has the property  $R'R = R^{-1}R = I_k$ . Using the definition  $A_0^{-1} = \text{chol}(\Sigma)R$  in equation (1), I obtain the structural shocks  $\varepsilon_t$  as follows:

$$u_t = A_0^{-1}\varepsilon_t \quad (5)$$

$$\Leftrightarrow \varepsilon_t = R'\text{chol}(\Sigma)^{-1}u_t \quad (6)$$

I choose the angle of  $R$  by randomly drawing candidates from a domain between 0 and  $2\pi$ . In case the sign restrictions described above are met, I keep the draw and otherwise discard it. I stop the search once I have collected 200 accepted angles.

This identification has the clear disadvantage that the 200 accepted angles imply 200 observationally equivalent but different and possibly conflictive models. To circumvent this problem and find a “representative” model, I follow the “Median Target Approach” by Fry et al. (2007): I compute the impulse response functions

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<sup>6</sup>The time horizon for which the sign restrictions are imposed on the impulse response functions is set to four quarters. Hence, after that period the impulse responses are unrestricted. I tried different horizons but the estimation results did not significantly change.

implied by all 200 accepted angles and choose the one that minimizes the squared distance from the median impulse responses.

## 5. Results

In this section, I present key results implied by the FAVAR. First, I perform an impulse response analysis to learn about the domestic and international effects of the Chinese structural shocks. Then I show the estimated shock series to depict the Chinese business cycle of the last decade in terms of AS and AD innovations. Finally, I assess the international effects of these innovations from 2012 onward using historical decompositions of inflation and interest rates outside of China.

### 5.1. Impulse response functions

Figure 3 shows cumulative median impulse responses of Chinese GDP growth and inflation to a positive AS shock and a positive AD shock. Both shocks are scaled such that Chinese GDP growth increases on impact by one standard deviation, which is 0.6 percent. To account for measurement uncertainty, I add 68 and 95 percent confidence intervals to the median impulse responses resulting from the bootstrap-after-bootstrap method of Kilian (1998). I set the number of bootstrap replications to 1000. Since  $n \gg T$  the uncertainty associated with the factor estimation can be neglected, as shown by Bai et al. (2006).

As expected, the AS shock drives GDP and prices in China in opposite directions. It increases GDP by 0.6 percent on impact and by 1.3 percent in the long run, and it lowers the GDP deflator by up to 0.8 percent. The AD shock, by contrast, drives GDP and prices in the same direction. GDP again increases by 0.6 percent on impact and slowly fades out afterwards. Prices react more sluggishly to the AD shock than to the AS shock: The GDP deflator appreciates by

0.8 percent on impact and reaches its maximum of 2.9 percent only six quarters after the shock.

Figures 4 and 5 show how global oil, commodity, and steel prices and national price indicators outside of China react to the Chinese shocks. As national reference measures I use consumer and producer prices (CPI and PPI). Since it is impossible to comment on the impulse response functions of all 41 countries in the dataset I compute weighted averages over countries for Asia (Japan and South Korea), the eleven original Euro Area countries, eight non-Euro countries (Czech Republic, Denmark, Hungary, Norway, Poland, Sweden, Switzerland, and the UK), and Oceania (Australia and New Zealand). The weights are based on the country shares in the group-specific nominal GDP aggregates.

The figures show that the impulse response functions have qualitatively similar features across price categories and country groups. Most impulse responses are close to zero or insignificant at small horizons, which implies that international spillovers of Chinese business cycle shocks are sluggish. They reach their maximum after approximately four quarters and become insignificant again at large horizons. Hence, the Chinese shocks do not have long-run effects on international prices.

The figures also show that the AS shock tends to have a lowering on-impact effect on prices outside of China, which either fades out or turns slightly positive after approximately one year. This finding might be the result of two countervailing mechanisms: By definition, a positive AS shock lowers inflation but raises real activity in China. Through international price competition this should also lower prices outside of China. However, if higher real activity comes along with higher demand for commodities and thus raises their prices, the net effect of the AS shock is unclear.

By contrast, the AD shock has a considerable and significantly positive effect on global prices. The effects are particularly large for oil, commodity, and steel prices, which respectively increase by ten, three, and eight percent. Hence, globally traded raw materials are important transmission channels of Chinese demand shocks. We also see that the national PPIs react considerably stronger to a Chinese AD shock than the CPIs, a finding which is in line with Eickmeier and Kühnlenz (2016). Overall, the effect is most pronounced in the US, where the PPI increases by three percent in response to a Chinese AD shock. In Asia, the Euro Area, the non-Euro countries, and Oceania the effects are also non-negligible and amount to 2.3, 1.4, 2.0, and 1.3 percent, respectively. The greater importance of external shocks for the PPIs might be explainable by the fact that the PPI contains more tradeable and manufactured goods than the CPI. Furthermore, Bacchetta and Wincoop (2003) show that if domestic firms import intermediate goods priced in foreign currency and sell final goods in domestic currency, the pass-through of external shocks to the CPI is incomplete.

### *5.2. Structural shock estimates*

Figure 6 displays 3-quarter averages of the estimated Chinese AS and AD shock series. The series indicate for each point in time whether the shocks are expansive or contractionary and which magnitude they have.

The Great Recession that affected China already in 2008 is preceded by positive AS and AD shocks from 2006 until the beginning of 2008. The shock sizes in 2008 and 2009 are rather moderate, which is expected since the Great Recession is largely explained by the international component  $H_t$ . The recovery of 2010, however, also shows up as positive demand innovations in China.

Afterwards, we observe a further expansion in demand in 2012 and 2013, fol-

lowed by a sharp downturn from mid-2014 until 2015Q1. The AD component then recovers slightly in 2015 and 2016 and turns positive again in 2017. The AS component persistently stays at low levels after the Great Recession and turns positive only in mid-2011. After an expansive period until the end of 2014, it becomes contractionary again and remains so until the end of the sample.

To sum up, China's cyclical downturn from 2012 until 2015 can be attributed to a mixture of negative AS and AD shocks. The further fall in real activity and the trend reversal in the inflation rate in 2016 and 2017 is mainly due to negative AS shocks.

### *5.3. Historical decompositions*

In this section, I quantify the global influence of the Chinese shocks on inflation and interest rates after 2012. The figures 7 and 8 show historical decompositions of several inflation indicators. Each panel shows the realized inflation rate (solid) and a hypothetical rate (dashed) that results from a counterfactual analysis. In that counterfactual analysis, I maintain the idiosyncratic and common shocks in the FAVAR but shut down one of the two Chinese shocks or both shocks. Hence, the difference between the realized and the hypothetical rates indicates how relevant China's influence was for global inflation. To examine the financial implications, I perform the same historical decompositions for interest rates (see Figure 10). As region-specific aggregate measures I again take the weighted averages of the national indicators.

#### *5.3.1. Inflation*

The Figures 7 and 8 indicate a non-negligible impact of the Chinese business cycle on global inflation dynamics during the last decade. The hypothetical inflation rates without the influence of one of the two Chinese shocks are to a moderate



but significant degree different from the realized rates. The same holds for the hypothetical rates where both shocks are shut down at a time.

Figure 7 shows that after 2014, the Chinese shocks tended to lower global oil, commodity, and steel prices since the hypothetical inflation rates are higher than the realized rates. Before 2014, the Chinese shocks had negligible or even positive effects since the hypothetical rates are lower than the realized rates. This finding again confirms that commodity prices are important transmission channels of Chinese business cycle shocks.

If we look at national CPI and PPI inflation outside of China, displayed in Figure 8, the results are similar. Until 2014, the effects of the Chinese shocks are ambiguous or economically insignificant. After 2014, the negative AS and AD shocks take effect and markedly lower inflation rates in all country groups. The results confirm the findings from section 5.1: first, the effects are most pronounced in the US. Second, AD shocks have slightly larger effects than AS shocks, and third, the PPIs react stronger to both Chinese shocks than the CPIs. Between 2014Q1 and 2017Q4, the realized quarterly PPI inflation rates in Asia, the Euro Area, the non-Euro countries, Oceania, and the US were on average 0.16, 0.18, 0.16, 0.19, and 0.33 percentage points lower than the hypothetical rates without the two Chinese shocks. These numbers are considerable given that the standard deviations of the quarterly PPI inflation rates over the entire sample are 0.99, 1.04, 1.17, 1.33, and 1.74 percent, respectively. In terms of CPI inflation rates the differences are slightly smaller in the same period. The realized CPI inflation rates were on average 0.01, 0.06, 0.06, 0.06, and 0.10 percentage points lower than the hypothetical rates in Asia, the Euro Area, the non-Euro-Area countries, Oceania, and the US, respectively. The country group-specific standard deviations of CPI

inflation amount to 0.34, 0.29, 0.32, 0.34, and 0.53 percent.

These effects are clearly linked to the positive AD shocks in 2012 and 2013 and the negative AD shocks in 2014 and 2015. It is striking that the Chinese influence on international prices was particularly significant in the second half of 2015, hence about one year after the period of large negative AD shocks from 2014Q2 until 2015Q1. This time lag is due to the sluggishness of the international effects that I found in section 5.1.

To assess the cumulative effect of the Chinese shocks, I also compute price levels implied by the historical decompositions. Figure 9 displays the price levels implied by the hypothetical inflation rates that include all shocks but the two Chinese in the FAVAR. Besides, it shows the realized price levels. I normalize all prices in 2014Q1 to an index value of 100<sup>7</sup>. Table 2 additionally reports the gaps between the realized and the hypothetical prices in 2015Q4, 2016Q4, and 2017Q4.

The results show that in the first half of 2014, China's global influence on prices was still small. Afterwards, however, the contractionary Chinese shocks become increasingly visible since realized and hypothetical prices start to diverge. The effect on the price of raw materials is especially pronounced: In terms of steel prices it amounted to -8.3 percent already in 2015Q4. The national price indicators reacted a bit later but still noticeably. In the US, for example, the CPI and the PPI fell by up to 1.8 and 5.7 percent in response to the Chinese shocks, respectively. In the Euro Area and Asia, China's influence was strong enough to turn (hypothetically) positive dynamics of the PPI into negative. Whereas the

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<sup>7</sup>I choose this date as base period because in 2014Q2 the Chinese AD shock fell sharply below zero, reaching its lowest level in 2015Q1. Furthermore, in 2014 at the latest the Chinese shocks started to markedly lower inflation rates outside of China, as the figures 7 and 8 show.

realized PPI in these regions dropped by 0.7 and 1.0 percent, the counterfactual PPIs without the Chinese shocks would have increased by 2.5 and 1.2 percent, respectively.

### *5.3.2. Interest rates*

In this section, I examine to which degree the Chinese shocks spilled over to interest rates outside of China. Similarly like inflation rates, interest rates experienced a pronounced and persistent decline after the Great Recession. While parts of this decline can be explained by a lower real interest rate (Holston et al., 2017), monetary policy rules and the Fisher effect create a direct link to domestic inflation (Taylor, 1999; Clarida et al., 1999; Mishkin, 1992). Moreover, since the findings from sections 5.1 and 5.3.1 suggest a significant contribution of Chinese shocks to the global downturn in inflation rates, I conclude that these shocks should also have lowered interest rates internationally.

I conduct the same historical decomposition of interest rates as in the case of inflation rates. Figure 10 displays 10-year government bond rates in the considered regions and their respective counterfactuals without the influence of the two Chinese shocks<sup>8</sup>. The comparison between both series shows that the Chinese business cycle noticeably affected long-term interest rates outside of China. Between 2012 and 2017, the average absolute deviation between the realized interest rate and the hypothetical rate amounted to 12, 13, 14, 18, and 12 basis points in Asia, the Euro Area, the non-Euro countries, Oceania, and the US, respectively. From 2013Q1 until 2015Q1, the realized rates tended to be higher than the hypothetical rates, which implies a positive effect of the Chinese shocks during this time. After

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<sup>8</sup>I conducted the same analysis using interest rates with shorter maturity (e.g., 3-month rates) but did not find significantly different results.

2015Q1, the effect becomes negative. This reversal follows the qualitative turn of the Chinese AD shock from positive to negative in 2014Q2 and is consistent with the effects on inflation described in section 5.3.1. The lowering impact is most visible in the last observations. In the Euro Area, for instance, the difference between the realized 10-year rate and the counterfactual without the Chinese influence amounted to 28 basis points in 2017Q4.

To sum up, China's cyclic downturn also spilled over to interest rates and thus the financial sector outside of China. In particular, it reinforced the decline in financial yields during the last decade, resulting in a significant reduction at the current edge.

#### *5.4. Robustness checks*

As customary in empirical papers, I perform several sensitivity checks to strengthen the credibility of my results. In the following subsections, I present results from modifying a single property of the baseline FAVAR and re-estimating it. In every modification the respective other estimation settings remain unchanged. I check the sensitivity of the baseline setup by comparing the cumulative effects of the Chinese shocks on global inflation in 2016Q4. All results are reported in Table 3.

##### *Ordering of variables*

To orthogonalize the VAR residuals in the baseline setup, I set the Chinese variables below the international factors. Hence, I assume that the international factors react to shocks from China only with a delay of one quarter whereas the Chinese variables immediately react to international shocks. In a first experiment, I check if this ordering plays a role for my results and conclusions. I estimate a version of the FAVAR in which I set the Chinese variables above the international

factors and again compute the cumulative effects of the Chinese shocks on international prices. The results are reported in the second row of Table 3, together with the baseline results. As it turns out, the new ordering leads to higher cumulative effects of the Chinese shocks on prices outside of China. These findings are not unexpected since the alternative ordering allows international factors to react to the shocks on impact. As a result, my conclusion that China's economic slowdown has lowered prices globally is confirmed.

### *Detrending*

As the data showed, the slowdown in China's economic performance markedly contrasts with the very high and stable growth rates before the Great Recession. The stark difference between both periods raises the question whether not only China's business cycle has slowed down but also its long-term potential growth. If this is the case, however, the Chinese series need to be cleaned by a time-varying trend prior to using them in the FAVAR. Up to this point, I only adjusted the growth rates by their means, implicitly assuming constant potential growth.

To allow for a secular growth trend, I apply the local-level model suggested by Stock and Watson (2005) to the Chinese GDP growth rate and the inflation rate. The model yields a smooth time-varying trend for both series, which I subtract from these. Then I plug the detrended series into the FAVAR and carry out the estimation as described. The estimated trend is shown jointly with the other series in the FAVAR in Figure 11.

The effects of the Chinese shocks under this modification are presented in row two of Table 3. As it turns out, they are barely distinguishable from the baseline results, which suggests that time-variation in the growth trend does not play a role in this paper.

### *Long-run restrictions*

In section 4, I described and justified the identification of AD and AS shocks in China by means of short-run sign restrictions. To check if my results hinge on this scheme, I apply long-run restrictions to identify both shocks. Blanchard and Quah (1989) introduced this method relying on the idea that AD shocks should have no long-run effects on real economic activity. I follow their assumption and impose on the Chinese AD shock that it does not affect Chinese GDP in the long run. By contrast, the effect of the AS shock is left unrestricted. The estimated impact of both shocks on international prices are displayed in row four of Table 3. They are slightly smaller in absolute values but still very similar to those of the baseline setup. I conclude from this that the identification of structural shocks plays a subordinate role in my conclusions.

### *Control for oil prices*

Here I address the argument that oil market developments might not be sufficiently accounted for in the model, especially during the sharp decline in oil prices in 2014. Between June and December of that year, the Brent oil price dropped by 44 percent of its original value. According to Baumeister and Kilian (2016), half of this decline can be attributed to a fall in global aggregate demand, whereas one third was due to oil supply shocks. Since oil supply shocks should have opposite effects on GDP and inflation, I need to rule out the risk that they are confused with Chinese AS shocks. To control for oil supply shocks, I replace the factor space by  $F_t = [\hat{H}_t', \Delta cgdpt, \Delta cdefl_t, \Delta oilp_t]'$  where  $oilp_t$  denotes the real price of crude oil, and re-estimate the model. The fact that oil prices are ordered last follows the assumption that they are fast-moving and is consistent with the discussion in section 4.

The estimation results under this setup are reported in the fifth row of Table 3. It turns out that controlling for oil price shocks slightly increases the effect of China's growth slowdown on global inflation. This finding is to a considerable degree due to the third and fourth quarters of 2014, hence the period in which the oil price drop occurred. However, the total effects are still comparable to those in the baseline setup and therefore do not affect my conclusions.

#### *Control for the Euro crisis*

I also address the possibility that the global factors  $\hat{H}_t$  do not sufficiently control for the Euro crisis, which kicked in between 2012 and 2013 in terms of Euro Area GDP and thus overlapped with China's economic slowdown. To account for this issue, I add Italian real GDP growth ( $\Delta itagdp_t$ ) as a slow-moving variable to the factor space such that  $F_t = [\hat{H}_t', \Delta itagdp_t, \Delta cgdpt, \Delta cdefl_t]'$ , and re-estimate the model then. I choose Italian GDP growth for two reasons: First, Italy is the third-largest economy of the Euro zone. Second, Italy was severely and persistently affected by the crisis: National GDP growth was -2.8 percent in 2012 and -1.7 percent in 2013. It turns out, however, that re-running the estimation based on this specification yields only negligible changes (see row six of Table 3).

#### *Regional factors*

It is a popular narrative in the literature that regional factors are important drivers of the international business cycle (see, e.g., Artis and Zhang, 1999 and Stock and Watson, 2005). To account for this issue, I modify my model setup as follows: I estimate a total of ten regional factors, namely four for North America and Europe and two for Asia (excluding China). The factors are estimated by

extracting principal components from the region-specific subsamples of  $X_t$ <sup>9</sup>. Then I set up the factor space  $F_t = [\hat{H}_t^{EU'} \quad \hat{H}_t^{NA'} \quad \hat{H}_t^{AS'} \quad \Delta cgdp_t \quad \Delta cdefl_t]'$  and re-estimate the FAVAR. I tried different orderings of the regional factors, but the results were barely distinguishable from those presented here. The cumulative effects of the Chinese shocks in the historical decomposition are reported in row seven of Table 3. Again, except for a few cases, the numbers are very similar to those of the baseline estimation.

#### *Measuring real activity*

Since the quality of Chinese data is often subject to criticism, I check if using Chinese value-added instead of real GDP in the FAVAR yields different results. I again rely on the data constructed by Chang et al. (2016), which matches the series published by the World Bank. The growth rate of value-added is generally very similar to GDP growth but slightly differs in 2016 and 2017. In 2016, GDP growth amounted to 5.4 percent, but value-added grew by 6.5 percent. In 2017, GDP growth added up to 4.5 percent, while the growth rate of value added was 6.6 percent. However, if I take value-added in the FAVAR I obtain cumulative effects of the Chinese shocks that are very similar to those of the baseline setup. The results are reported in row eight of Table 3.

#### *Lag order*

Finally, I check if a higher lag order in the VAR changes my results. I re-estimate the model with  $p = 3$ , as suggested by the AIC. However, I find that both the impulse responses and the structural shock series are very similar to

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<sup>9</sup>The number of factors is determined by the IC2 criterion by Bai and Ng (2002). I cleaned the regional factors from the Chinese component using the procedure described in section 4.



those of baseline setup with  $p = 2$ . The same holds for the cumulative effects of the Chinese shocks on global inflation, which are reported in row nine of Table 3. As it turns out, they are slightly larger in absolute values than those of the baseline setup. Hence, my conclusions remain intact.

## 6. Conclusion

I fit a factor-augmented vector autoregressive model to a large-dimensional macroeconomic data set covering 41 countries over the period 2000-2017 to examine the impact of China's economic downturn on inflation outside of China. I identify and estimate Chinese AS and AD innovations and compute impulse responses of global price indicators and national prices in the US, Europe, Asia, and Oceania in response to these innovations. Furthermore, I compute historical decompositions to identify the Chinese economic slowdown in terms of structural shocks and assess their contributions to international inflation dynamics.

My main findings are the following: (i) Business cycle shocks and especially AD shocks in China significantly spill over to national inflation rates in the US, Europe, Asia, and Oceania and are transmitted by global oil, commodity, and steel prices. (ii) The slowdown in the Chinese business cycle after the Great Recession can be attributed to a combination of contractionary AS and AD shocks in China. (iii) From 2014 onward, these shocks had a lowering effect on quarterly PPI inflation rates outside of China of up to 0.3 percentage points. They cumulatively lowered global oil prices by twelve percent and national PPIs outside of China by up to six percent. Hence, the Chinese business cycle noticeably contributed to the worldwide decline in inflation rates and hampered the recent upward trend. (iv) Adverse Chinese shocks also spilled over to interest rates and hence the financial

sector outside China, resulting in a lowering impact on the current level of yields.

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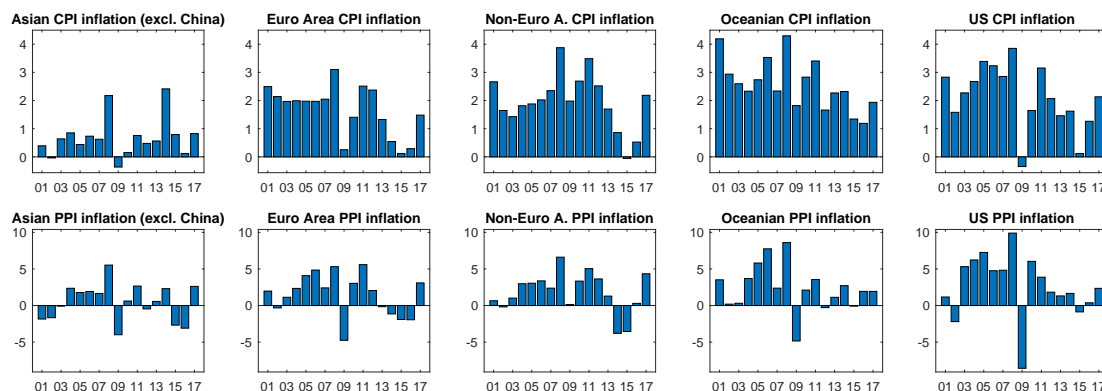
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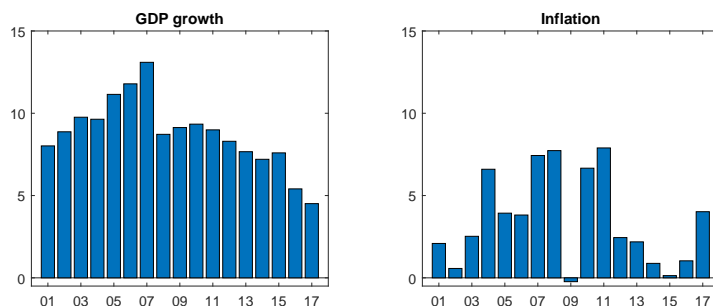
# Figures and Tables

Figure 1: Global inflation indicators



Notes: The panels show four-quarter averages of year-on-year inflation rates (in percentages). The national inflation rates are averaged over countries in Asia (Japan and South Korea), the eleven original Euro Area countries, eight non-Euro countries, and Oceania (Australia and New Zealand). The averages are weighted according to the countries' shares in the group-specific nominal GDP aggregates. Source: OECD and own calculations.

Figure 2: Chinese business cycle indicators



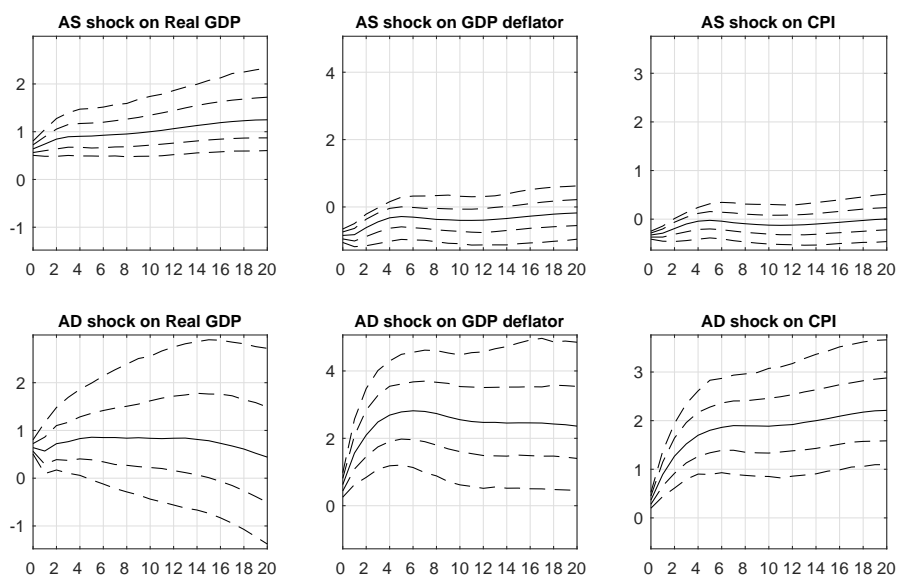
Notes: The panels show four-quarter averages of year-on-year growth rates of Chinese real GDP and the Chinese GDP deflator (in percentages). Source: Chang et al. (2016) and own calculations.

Table 1: Number of factors selection

Number of factors	1	2	3	4	5	6	7
Bai and Ng criterion IC2	-0.11	-0.18	-0.23	-0.26	<b>-0.28</b>	-0.27	-0.26
Explained variance in %	26.1	19.5	14.0	10.8	8.4	5.8	4.6

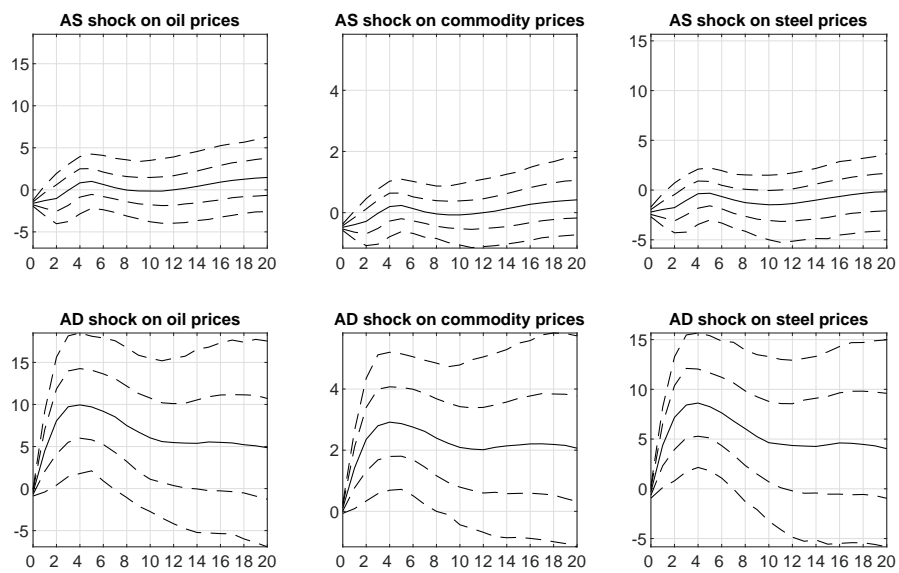
Notes: The upper row shows the Bai and Ng criterion IC2 for different numbers of factors. The factors are the first principal components of  $X_t$ . The lower row shows the variance shares of  $X_t$  explained by the respective factors.

Figure 3: Impulse response functions - Chinese indicators



Notes: The panels show cumulative impulse response functions of economic indicators to a Chinese AD shock and an AS shock, displayed in percentages. Both shocks are scaled such that Chinese GDP growth increases on impact by one standard deviation (0.6 percent). The impulse responses are constructed using the “Median Target Approach” suggested by Fry et al. (2007). The dashed graphs are 68 and 95 percent confidence intervals resulting from the bootstrap-after-bootstrap method proposed by Kilian (1998) and 1000 re-estimations.

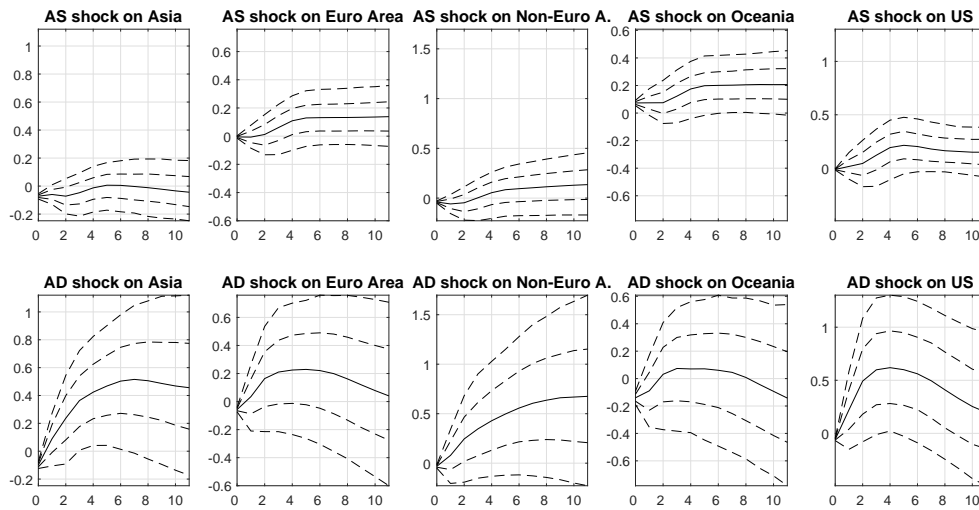
Figure 4: Impulse response functions - Global price indicators



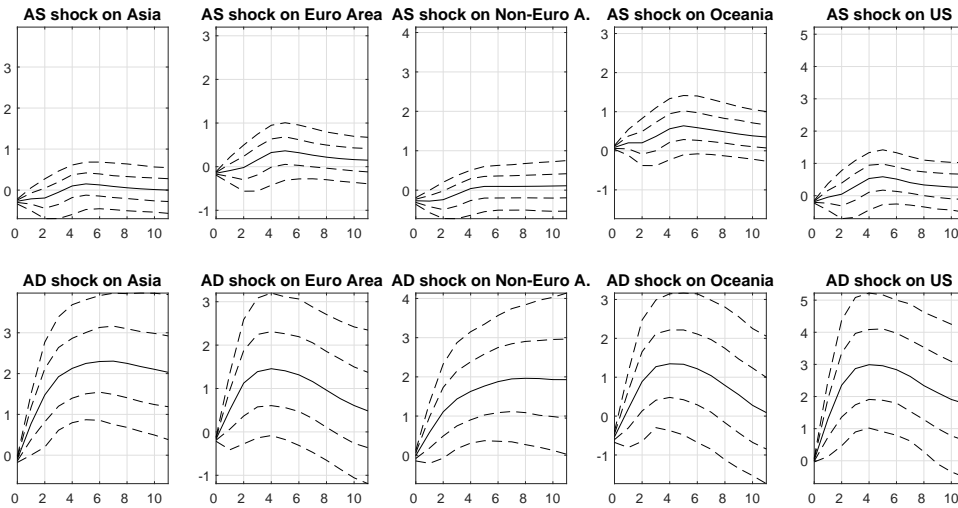
Notes: See figure 3 for a detailed description of the graphs.

Figure 5: Impulse response functions - National price indicators outside of China

(a) CPI



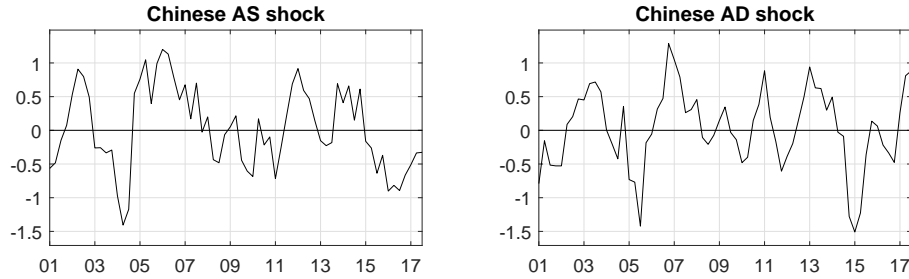
(b) PPI



Notes: See figure 3 for a detailed description of the graphs.

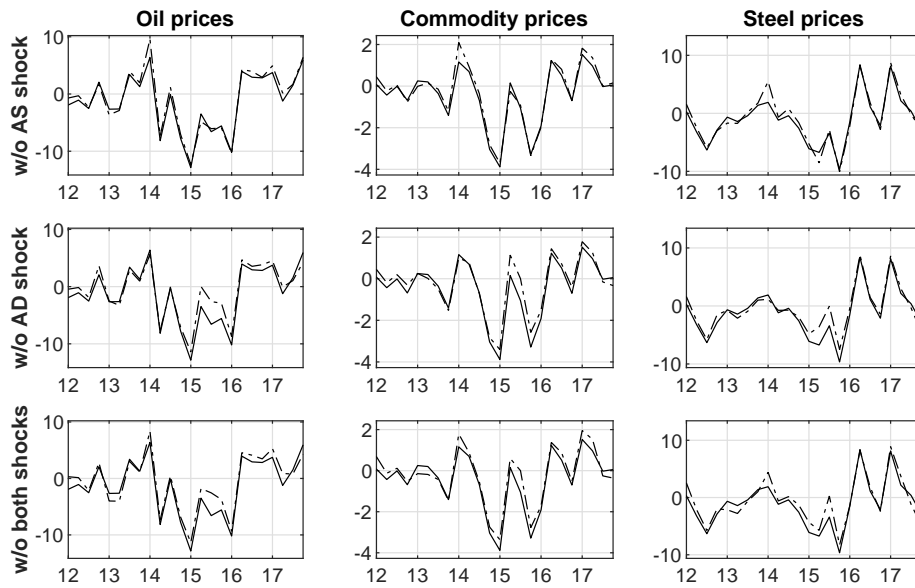


Figure 6: Structural shocks



Notes: The panels show 3-quarter averages of the estimated Chinese AS and AD shocks.

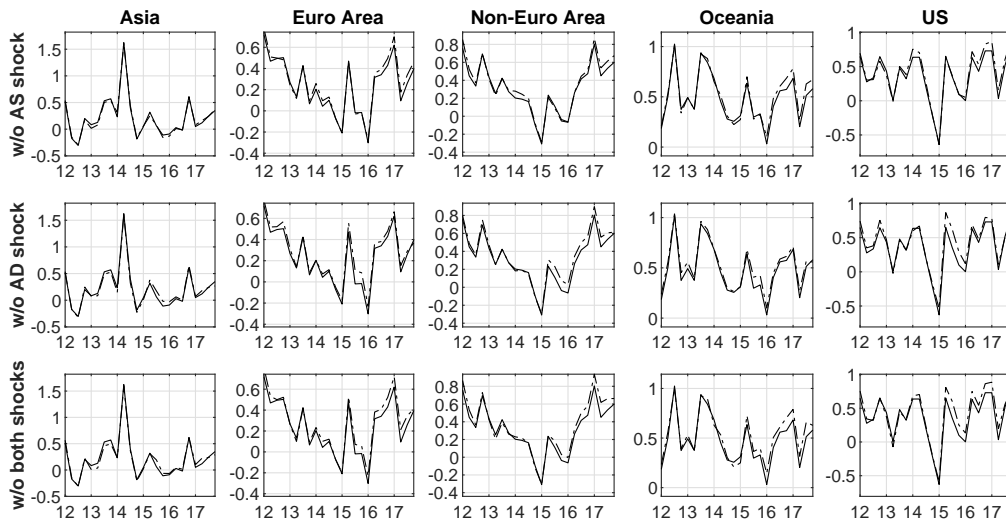
Figure 7: Historical decompositions - Global inflation indicators



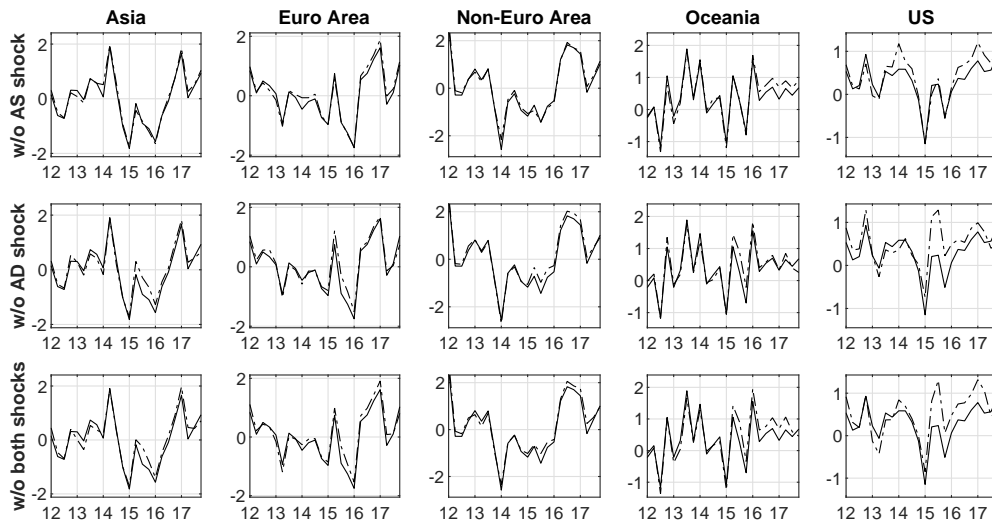
Notes: Each panel shows the realized quarterly inflation rate (solid) and a hypothetical inflation rate that is implied by the FAVAR (dashed). The hypothetical rates in the upper two rows result from a counterfactual analysis in which one Chinese shock is shut down and all other shocks are maintained. The hypothetical rates in the bottom row result from shutting down both Chinese shocks and maintaining all other shocks. The inflation rates are displayed in percentages.

Figure 8: Historical decompositions - National inflation indicators outside of China

(a) CPI inflation



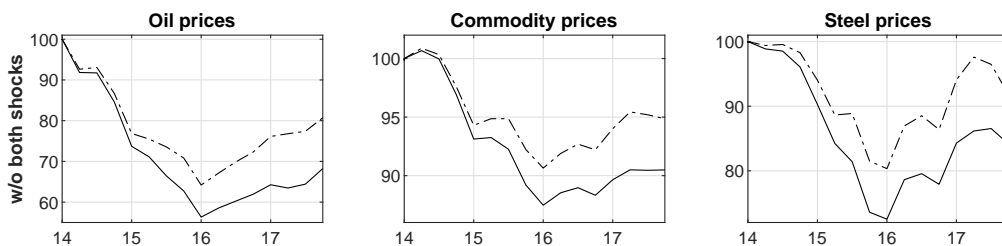
(b) PPI inflation



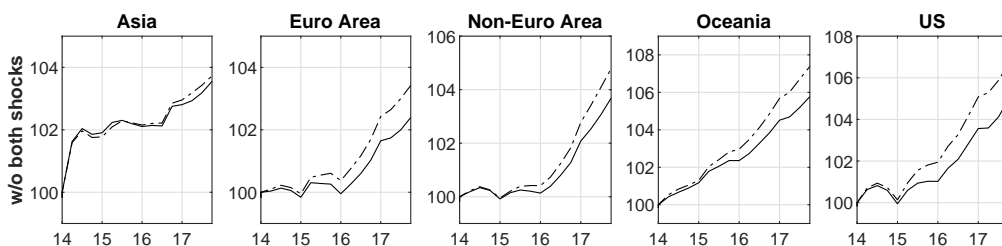
See figure 7 for a detailed description of the graphs.

Figure 9: Cumulative effects of Chinese shocks on prices outside of China

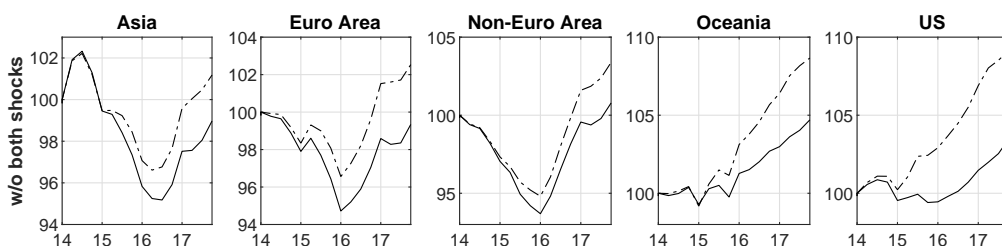
(a) Global price indicators



(b) CPI



(c) PPI



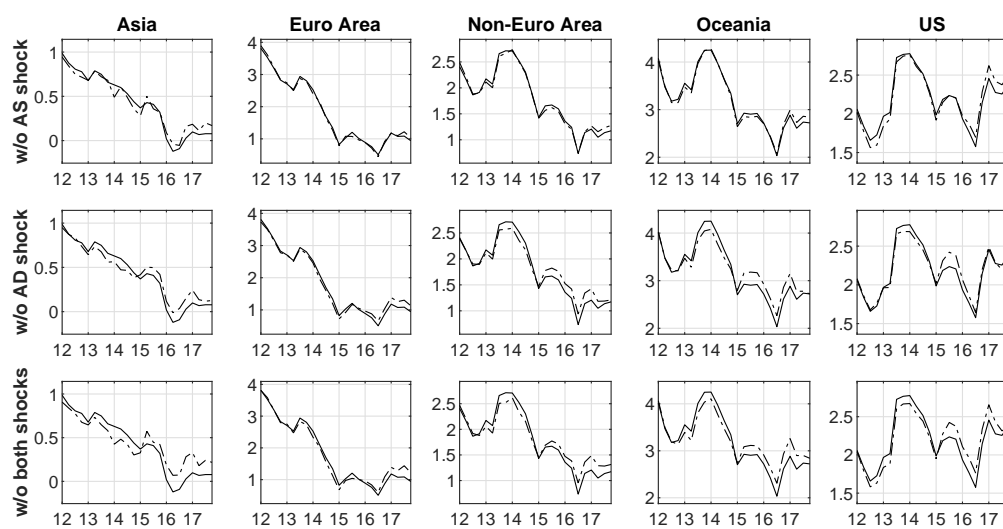
Notes: Each panel shows the realized price level (solid) and the price level implied by a hypothetical quarterly inflation rate (dashed). The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

Table 2: Cumulative effects of Chinese shocks on prices outside of China

Global prices	Oil prices	Commodity prices			Steel prices
2015Q4	-8.7		-3.2		-8.3
2016Q4	-10.7		-4.0		-8.5
2017Q4	-12.4		-4.4		-7.2
National prices	Asia	Euro Area	Non-Euro	Oceania	US
CPI					
2015Q4	-0.06	-0.39	-0.26	-0.51	-0.85
2016Q4	-0.12	-0.72	-0.61	-1.08	-1.40
2017Q4	-0.17	-1.08	-1.17	-1.69	-1.77
PPI					
2015Q4	-1.23	-1.79	-1.11	-1.58	-3.24
2016Q4	-1.82	-2.71	-1.79	-3.18	-4.96
2017Q4	-2.21	-3.30	-2.66	-4.12	-5.70

Notes: The table displays the difference between the realized price level and the price level implied by a hypothetical quarterly inflation rate. The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

Figure 10: Historical decompositions - National interest rates outside of China



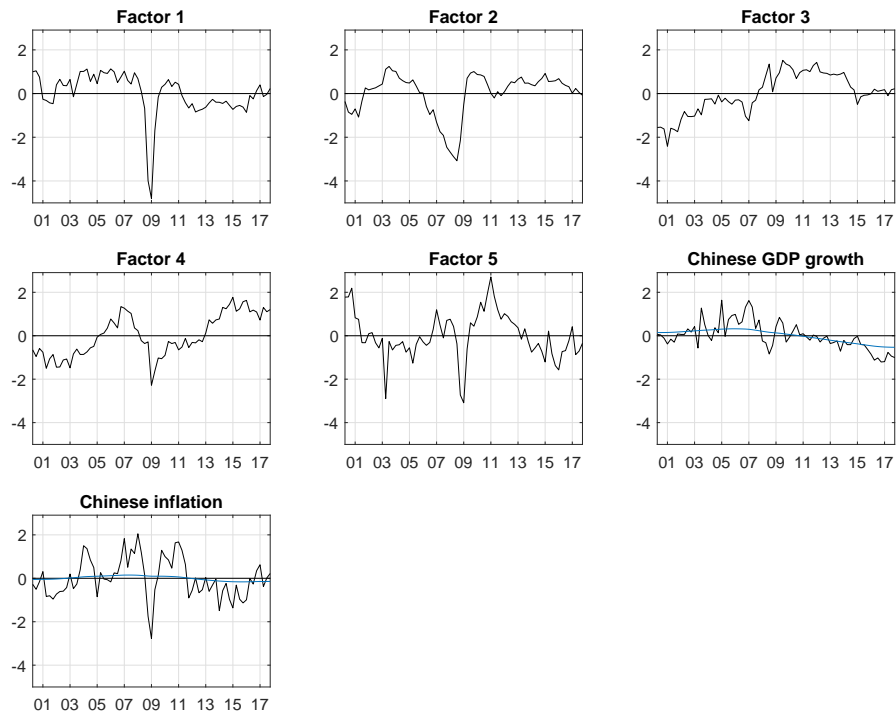
Notes: Each panel shows the realized 10-year government bond rate (solid) and a hypothetical rate that is implied by the FAVAR (dashed). The hypothetical rates in the upper two rows result from a counterfactual analysis in which one Chinese shock is shut down and all other shocks are maintained. The hypothetical rates in the bottom row result from shutting down both Chinese shocks and maintaining all other shocks. The rates are displayed in percentages.

Table 3: Robustness checks

Modification	Asia (excl. China)	Euro Area	Non-Euro Area	Oceania	US
CPI					
1. <b>Baseline</b>	-0.12	-0.72	-0.61	-1.08	-1.40
2. Ordering of variables	-0.09	-1.45	-2.03	-1.80	-1.54
3. Detrending	-0.08	-0.70	-0.56	-1.06	-1.41
4. Long-run restrictions	-0.10	-0.67	-0.55	-1.02	-1.35
5. Control for oil prices	-0.12	-1.26	-1.14	-1.61	-2.17
6. Control for Euro crisis	-0.13	-0.63	-0.53	-0.99	-1.27
7. Regional factors	-0.06	-0.80	-0.84	-1.00	-1.21
8. Value-added	-0.10	-0.65	-0.52	-1.05	-1.41
9. VAR(3)	-0.40	-1.06	-1.08	-0.93	-1.55
PPI					
1. <b>Baseline</b>	-1.82	-2.71	-1.79	-3.18	-4.96
2. Ordering of variables	-1.64	-3.44	-3.74	-2.36	-3.48
3. Detrending	-1.69	-2.60	-1.65	-3.06	-4.92
4. Long-run restrictions	-1.74	-2.58	-1.67	-3.04	-4.83
5. Control for oil prices	-2.87	-3.86	-3.17	-4.03	-7.63
6. Control for Euro crisis	-1.69	-2.43	-1.61	-2.97	-4.55
7. Regional factors	-1.51	-2.67	-2.02	-1.68	-4.52
8. Value-added	-1.69	-2.44	-1.70	-3.00	-4.97
9. VAR(3)	-2.34	-4.49	-6.31	-2.01	-5.07

Notes: The table displays the difference between the realized price level and the price level implied by a hypothetical quarterly inflation rate in 2016Q4. The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

Figure 11: Factors



Notes: The panels show the series used in the baseline FAVAR. The Chinese GDP growth and inflation rates are mean-adjusted and displayed jointly with their trends. The estimation of the trends is outlined in section 5.4.