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Abstract

I fit a high-dimensional macroeconomic dataset of 41 countries to a factor-augmented vector autoregressive model to examine the role of the recent Chinese economic slowdown for international inflation dynamics. I identify Chinese supply and demand shocks and examine their contributions to international price indicators. My main findings are: (i) Impulse response analyses indicate that Chinese business cycle shocks and especially demand shocks significantly spill over to inflation rates in Europe, North America, Asia and Oceania, mainly transmitted through global oil, commodity and manufacturing prices. (ii) The Chinese growth slowdown that started in 2012 can be attributed to a fall in aggregate Chinese demand and supply. (iii) Historical decompositions indicate that the fall in Chinese demand lowered national prices in Europe, North America, Asia and Oceania by up to 12 percent from the third quarter of 2013 on.

Keywords: China's Economic Slowdown, Global inflation, Spillovers, Factor Augmented Vector Autoregressive Model

JEL classification: E31, F44, F62

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1. Introduction

The rise of China to the world's second largest economy has aroused interest in how Chinese business cycle shocks spill over to the world economy, especially to the advanced economies in Europe and North America. There is a handful of empirical studies that have examined this question and all of them find that the spillovers are generally non-negligible and affect especially nominal variables. Eickmeier and Kühnlenz (2016), for example, find that the share of Chinese demand shocks amounts to eleven percent in the variance of crude oil prices and five percent in the variance of consumer prices. Dreger and Zhang (2011) additionally examine spillovers on real variables. They find that an increase in Chinese GDP has a substantial impact on output growth in the advanced economies, especially in Asia.

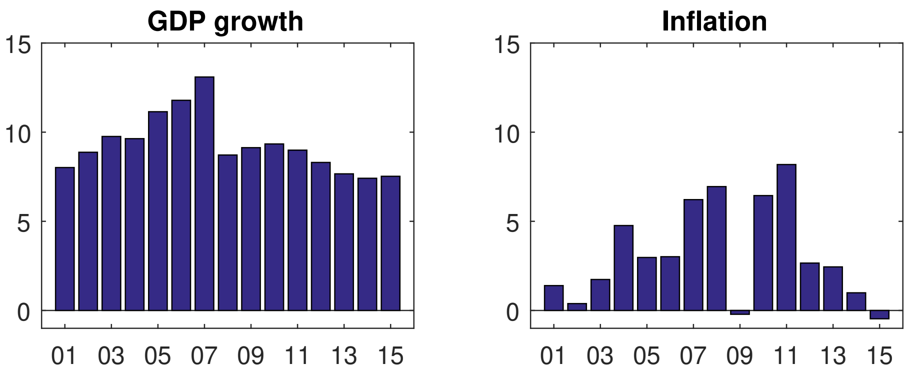
However, surprisingly low attention has been paid to the Chinese economic slowdown of the recent years and its effects on the international macroeconomy. Figure 1 illustrates this slowdown in terms of Chinese GDP growth rates and inflation. From 2001 to 2007 Chinese GDP growth rates increased steadily to a maximum of 13.1 percent. In 2008 the Great recession kicked in and reduced GDP growth to 8.7 percent. After a weak recovery in 2009 and 2010 growth constantly fell again, from 9.3 in 2010 to 7.5 percent in 2015. For 2016, 2017 and 2018 the numbers are even lower. In 2016, the IMF estimates annual GDP growth at 6.7 percent and predictions for 2017 and 2018 point to 6.8 and 6.5 percent, respectively[1].

Chinese inflation rates seem to lag behind GDP growth for at least one year. Whereas the Great recession affected GDP growth in 2008 inflation slumped only in 2009. Afterwards, rates increased again to 8.2 percent in 2011 and then fell continuously to a minimum of -0.5 percent in 2015. For 2016, the IMF estimates annual inflation to 1.1 percent.

Taken together, I confirm a substantial and persistent decline in the growth rates of real activity and prices which started in 2011 and 2012, respectively. Since the literature has found significant effects of Chinese business cycle shocks on the advanced economies it is natural to ask to which extent the slowdown is associated

[1] World Economic Outlook (WEO), International Monetary Fund, October 2017

Figure 1: Chinese descriptives



Notes: The panels show 4-quarter averages of year-on-year growth rates of real GDP and the GDP deflator. Source: Chang et al. (2016) and own calculations.

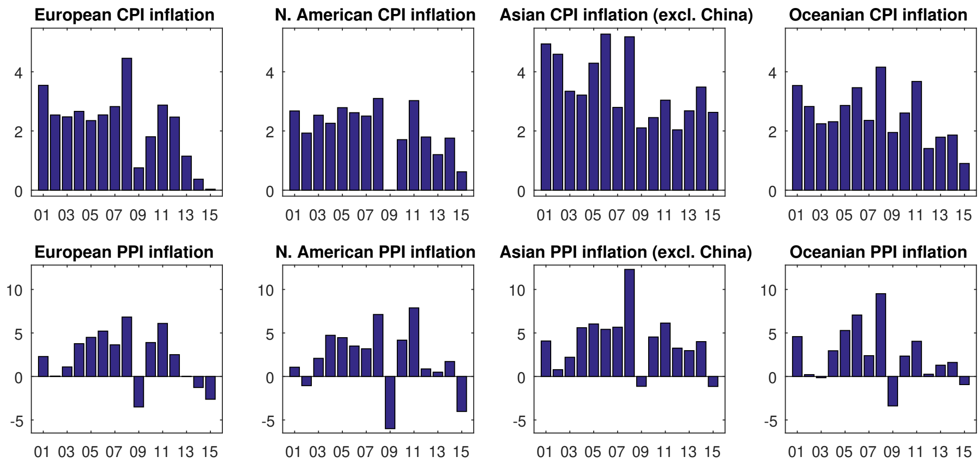
with contemporaneous economic events in these countries. One of these events is the pronounced fall in European and North American inflation rates from 2013 to 2015.

Figure 2 reports year-on-year consumer (CPI) and producer price (PPI) inflation rates for Europe, North America, Asia (without China) and Oceania. It shows how inflation rates slumped in all four regions during the crisis of 2009 and recovered again in 2010 and 2011. From 2011 onwards, they fell again but continuously until 2015. In North America, CPI inflation rates fell from 3.0 percent to 0.6 percent. In terms of PPI inflation the decline was even stronger, from 7.9 percent in 2011 to -4.0 percent in 2015. This dynamics can be observed for both price indicators and in all regions with the only exception of Asian CPI inflation which remained stable at an average of 2.7 percent after 2011[2]. Hence, the Chinese economic slowdown is contemporaneous with the fall in European, North American and Oceanian inflation rates from 2011 on.

The aim of this work is to quantify the contribution of the Chinese economic slow-

[2]The fact that Asia was not deflating over the considered period can be attributed to increasing inflation rates in Indonesia and Japan. Between 2011 and 2015, Japanese CPI inflation increased from -0.3 percent to 0.8 percent in 2015, with a large spike in 2014 at 2.8 percent. Over the same period, Indonesian inflation increased from 5.4 percent to 6.4 percent. By contrast, India and Korea deflated from 8.9 and 4.0 percent in 2011 to 5.9 and 0.7 percent in 2015, respectively.

Figure 2: International descriptives



Notes: The panels show 4-quarter averages of year-on-year inflation rates. The national inflation rates are averaged over countries in Europe (EU + Norway + Switzerland), North America (US and Canada), Asia (Japan, Korea, India and Indonesia) and Oceania (Australia and New Zealand). Source: OECD and own calculations.

down for the inflation dynamics in these regions. To the best of my knowledge this issue has not been addressed in the literature yet. Dizioli et al. (2016) exclusively examine the spillovers from the Chinese slowdown to real variables of the five largest Asian economies and find that these spillovers are larger for those economies who are commodity exporters and have strong trade links with China (Malaysia, Singapore, and Thailand). Metelli and Natoli (2017) investigate the effects of the Chinese slowdown on inflation in the euro area and the United States using the NiGEM multi-country model. They show that the slowdown has led to a significant disinflation in developed countries. However, these results are based on different slowdown scenarios imposed on a theoretical model and not on the data.

I use a factor-augmented vector autoregressive model (FAVAR) that has been suggested by Forni et al. (2000). The FAVAR allows flexible economic modeling while keeping dimensionality manageable. I proceed as follows: First, I estimate a set of factors from a large dataset of 703 international macroeconomic series covering nominal and real variables of 41 major economies, including all OECD countries.

These factors then serve as control variables in a classical VAR model of Chinese GDP growth and inflation which represent the Chinese economy. I identify supply and demand shocks by imposing sign restrictions on the impulse response functions of Chinese GDP growth and inflation. To examine the international propagation of these shocks I provide impulse response functions of consumer and producer prices in North America, Europe, Asia and Oceania. Then I present the structural shock estimates which decompose China's economic slowdown in supply and demand shock components. Finally, the contribution of these shocks to international inflation is assessed by historical decompositions.

My main findings are: (i) Impulse response analyses indicate that Chinese business cycle shocks and especially demand shocks significantly spill over to inflation rates in Europe, North America, Asia and Oceania, mainly transmitted through global oil, commodity and manufacturing prices. (ii) The Chinese growth slowdown that started in 2012 can be attributed to a fall in aggregate Chinese demand and supply. (iii) Historical decompositions indicate that the fall in Chinese demand lowered national prices in Europe, North America, Asia and Oceania by up to 12 percent from the third quarter of 2013 on.

The rest of the paper is organized as follows: In section 2, I present the FAVAR framework. In section 3, I provide details of the data and their detrending. I describe the identification and estimation in section 4, the results of the impulse response analysis, the structural shock estimation, the historical decompositions and robustness checks in section 5. Section 6 concludes.

2. Factor-augmented vector autoregressive model (FAVAR)

Since I employ a high-dimensional dataset X_t of international macroeconomic indicators but only have a limited number of observations I cannot include all variables in a standard VAR model. Instead, I estimate a two-variable VAR of the Chinese economy that is augmented by a latent but estimable common component. Here I assume that the macroeconomic indicators are for the most part driven by common global and regional business cycles and therefore can be reduced to a handful of common factors. Including these factors in the VAR allows us to keep it parsimonious and at the same time to 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 on real variables.

I start with a classical structural VAR:

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

that can be represented in reduced form as

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

where $B_i = A_0^{-1} A_i$, $i = 1, \ldots, p$, and $u_t = A_0^{-1}\varepsilon_t$.

$F_t = [f_{1t} \ldots f_{kt}]' = [H_t' \quad \Delta cgdp_t' \quad \Delta cdefl_t']'$ is $k \times 1$-dimensional and consists of (latent) international factors H_t, Chinese GDP growth ($\Delta cgdp_t$) and the logarithmic difference of the Chinese GDP deflator ($\Delta cdefl_t$). Hence, if r is the number of the latent factors H_t and m the number of the observables $\Delta cgdp_t$ and $\Delta cdefl_t$ then $k = r + m$. As usual, it holds for the structural shocks ε_t and reduced-form shocks u_t that $\mathrm{E}(u_t) = \mathrm{E}(\varepsilon_t) = 0$, $\mathrm{E}(u_t u_t') = \Sigma$ and $\mathrm{E}(\varepsilon_t \varepsilon_t') = I$. The structural shocks ε_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 ε_t are described in section 4.

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

$$X_t = \Lambda' F_t + \Xi_t \qquad (3)$$

where Λ is the $n \times k$-dimensional loading matrix of the factors $f_{1t}, \ldots, f_{kt}$ and $\Xi_t = [\xi_{i,t} \ldots \xi_{N,t}]'$ are the idiosyncratic components. The f_t's are orthogonal both mutually and to the $\xi_{i,t}$'s. The $\xi_{i,t}$'s themselves are allowed to be weakly correlated between each others and over time in the tradition of Chamberlain and Rothschild (1983).

3. Data and detrending

The dataset X_t comprises $n = 703$ national macro series of 41 countries, namely all OECD countries plus Brazil, Indonesia, India, Lithuania, Russia and South Africa over the period 2000Q1-2015Q4. Hence, the number of observations is $T = 64$. For every country I include, if available, GDP, investment, consumption, 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 rates and 10-year rates, wages, unit labor costs, real effective exchange rates, employment and unemployment rates. In addition, I include the following international series: oil prices, fuel prices, commodity prices (excluding fuels) and manufacturing prices, stock market returns and their variance, inflation variance, world GDP, industrial production, trade volumes and the composite OECD leading indicator. The series are at a quarterly frequency and are taken from the OECD or national statistics offices. Both Chinese GDP growth and inflation are taken from Chang et al. (2016) who construct a standard set of quarterly macroeconomic time series comparable to those commonly used in the macroeconomic literature on Western economies. The main data source is the CEIC's China Premium Database, which compiles China's official macroeconomic time series.

All series except unemployment rates, interest rates, real effective exchange rates and variances are stationarized by taking logarithmic first differences. Since interest rates experienced a downward trend over the period considered they are linearly detrended. To prevent my results to be driven by large outliers I trim any observation that is further than five times the interquartile range away from its median to the respective threshold.

Although the sample covers the Great recession and the Chinese growth slowdown I assume a constant volatility regime in my model. I based most of my conclusions on historical decompositions, which are a function of both the variance matrix of the structural shocks $\mathrm{E}(\varepsilon_t \varepsilon_t')$, and the VAR coefficient matrices A_i. On the one hand, shifts in the relative variance of two structural shocks obviously 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 significantly change their results I conclude that heteroskedasticity is not a major issue for 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 natural choice but might be problematic if H_t is supposed to represent the international non-Chinese business cycle in the VAR system (1)-(2). It is quite possible 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 VAR of Chinese observables $\Delta cdefl_t$ and $\Delta cgdp_t$ which is augmented by these principal components 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) which isolates the international business cycle from the Chinese observables $\Delta cdefl_t$ and $\Delta cgdp_t$. The cleaning is executed as follows: First, I extract the first principal components of X_t and take these as a first estimate for the unobserved factors H_t, which I define as $\hat{H}_t^0$. The number of first principal components is determined by the $IC2$ criterion proposed by Bai and Ng (2002) and accordingly set to $r = 4$ (see Table 1). The explained variance of these principal components in X_t amounts to 69 percent. In the next step, I model $\hat{H}_t^0$ as a linear combination of Chinese and non-Chinese components:

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

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 substracting $b_{cdefl}\Delta cdefl_t + b_{cgdp}\Delta cgdp_t$ 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[3], which by assumption are predetermined with respect to $\Delta cdefl_t$ and $\Delta cgdp_t$. As is customary in the VAR literature, these variables are real variables and composite

[3]Here I again rely on the IC2 criterion of Bai and Ng (2002), which suggests three factors.

price indices. The remaining subset of fast-moving variables are accordingly the monetary aggregate M3, interest rates, stock market variables, oil and commodity prices (excluding fuels). Hence, real variables and composite price indices outside of China need at least one quarter to react to Chinese business cycle shocks whereas financial variables and commodity prices react instantaneously[4].

Table 1: Number of factors selection

Number of factors	1	2	3	4	5	6	7
Bai and Ng criterion IC2	-0.116	-0.188	-0.212	**-0.223**	-0.220	-0.207	-0.196
Explained variance in %	27.92	19.92	11.78	9.41	7.08	5.77	5.64

Notes: The upper panel shows the Bai and Ng criterion IC2 for different numbers of factors extracted by principal component analysis from X_t. The lower panel shows the shares of variance explained by different numbers of factors.

After estimating equation (4) by ordinary least squares I substract $b_{cdefl}\Delta cdefl_t + b_{cgdp}\Delta cgdp_t$ from $\hat{H}_t^0$ to compute the "cleaned" estimate $\hat{H}_t^1$.
The next step involves estimating Λ, which is carried out by regressing X_t on $\hat{F}_t = [\hat{H}_t^1 \quad \Delta cgdp_t \quad \Delta cdefl_t]$. This procedure is valid since principal components of X_t estimate its unobserved common component n-consistently and I accordingly do not face the problem of generated regressors. In order to examine internal spillovers of Chinese business cycle shocks (section 5.1) I also included key indicators of the Chinese economy as dependent variables in this regression.
I estimate the VAR system (1)-(2) by ordinary least squares, which gives me the reduced form residuals $\hat{u}$ and the residual covariance matrix $\hat{\Sigma}$. The lag length p is determined by the BIC and the HQ criterion which both point to $p = 1$[5]. To identify the structural shocks ε_t I impose two theory-based sign restrictions to the reduced-form shocks u_t. First, I orthogonalize them by the inverse of the

[4]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.

[5]Since the AIC suggests a higher lag order, I also estimate the VAR with $p = 4$. It turns out, however, that my results are not affected. Details are presented in section 5.4.

Cholesky factor of $\hat{\Sigma}$. Here I order the Chinese variables below $\hat{H}_t^1$ such that the Chinese variables react contemporaneously to all variables whereas $\hat{H}_t^1$ reacts to the Chinese shocks only with a lag of one quarter. This ordering is reasonable and

Table 2: Rotation

	Chinese supply	Chinese demand
Chinese GDP	+	+
Chinese Prices	−	+

consistent with the cleaning equation (4) with regard to the slow-moving variables, which form 67 percent of all variables in X_t. Since the fast-moving variables are assumed to react instantaneously to Chinese shocks I checked in Section 5.4 if ordering the Chinese variables before $\hat{H}_t^1$ alters my results. It turns out, however, that it does not play a role.

Second, I rotate the two orthogonalized Chinese shocks of Chinese GDP growth and inflation to identify a Chinese aggregate supply (AS) shock and a Chinese aggregate demand (AD) shock. I assume that these shocks meet the sign restrictions summarized in Table 2: Whereas the demand shock is allowed to drive Chinese GDP growth and inflation in the same direction the supply shock drives GDP growth and inflation in opposite directions[6]. 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 Givens rotation matrix R for which holds $R'R = R^{-1}R = I$. Using the definition $A_0^{-1} = \text{chol}(\Sigma)R$ in equation (2) I obtain

[6]The time horizon in which the sign restrictions are imposed on the impulse response functions is set to four quarters after the shock. Hence, after that period the impulse response functions are unrestricted. I tried different horizons and found that the estimation results do not significantly change.

the structural shocks ε_t as follows:

$$\begin{aligned} u_t &= A_0^{-1} \quad \varepsilon_t & (5) \\ \Leftrightarrow \varepsilon_t &= R' \quad \text{chol}(\Sigma)^{-1} \quad u_t & (6) \end{aligned}$$

I choose the angle α of R by randomly drawing candidates α_0 from a domain between 0 and 2π. In case the assumptions in table 2 are met I keep the draw of α_0 and otherwise I discard it. I stop the search once I have collected 200 accepted angles α_1.

This identification has the clear disadvantage that these 200 angles imply 200 different and possibly conflictive models that are observationally equivalent. To circumvent this problem and find a "representative" model I follow Fry et al. (2007). I compute the impulse response functions of all 200 accepted α_1s and choose the one that minimizes the squared distance from the median impulse responses.

5. Results

In this section I present key results from the estimated FAVAR. First, I perform an impulse response analysis to learn about the spillover effects of these shocks on the Chinese economy and international prices. Then I show the estimated series of the supply and demand shocks to discuss their effect on the Chinese business cycle. Finally, I carry out historical decompositions to quantify these spillover effects at different points in time. I place special emphasis on the question of how the recent Chinese growth slowdown has affected international inflation.

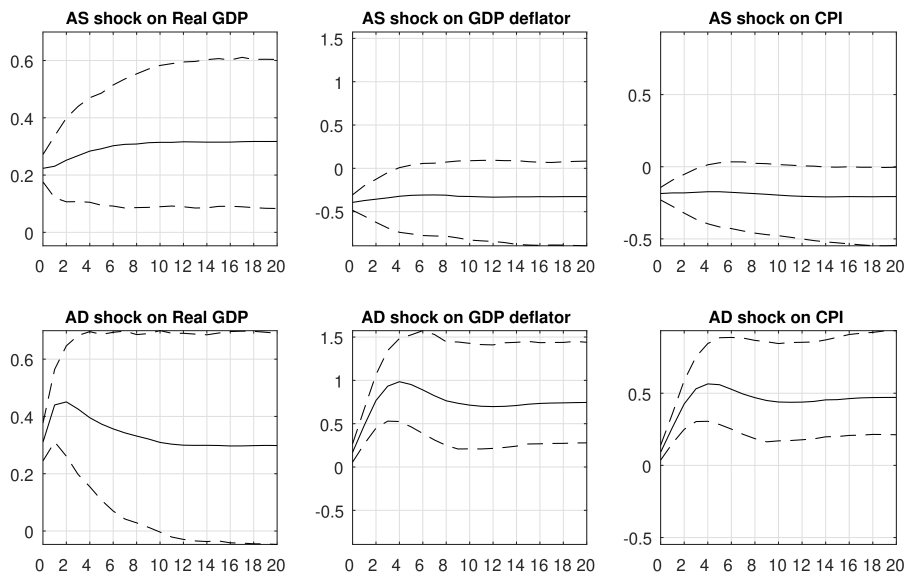
5.1. Impulse response functions

Figure 3 shows cumulative impulse responses of Chinese key variables to a one standard deviation increase in the Chinese supply and demand shocks. In order to account for measurement uncertainty I add 95 percent confidence intervals to the median impulse responses that result from the bootstrap-after-bootstrap method proposed by Kilian (1998). The number of bootstrap replications is set to 1000. Since $n > T$ the uncertainty associated with the factor estimation can be neglected, as shown by Bai et al. (2006).

As expected, the supply shock drives GDP and prices in the opposite direction. It increases GDP by 0.2 percent on impact and by 0.3 percent in the long run and permanently lowers the CPI by 0.2 percent. The demand shock, by contrast, drives GDP and prices in opposite directions. GDP increases by 0.3 percent on impact and by 0.5 percent after two quarters and slowly fades out then. The CPI reacts more sluggishly to the demand shock: It appreciates by 0.1 percent on impact and reaches its maximum of 1.0 percent only one year after the shock.

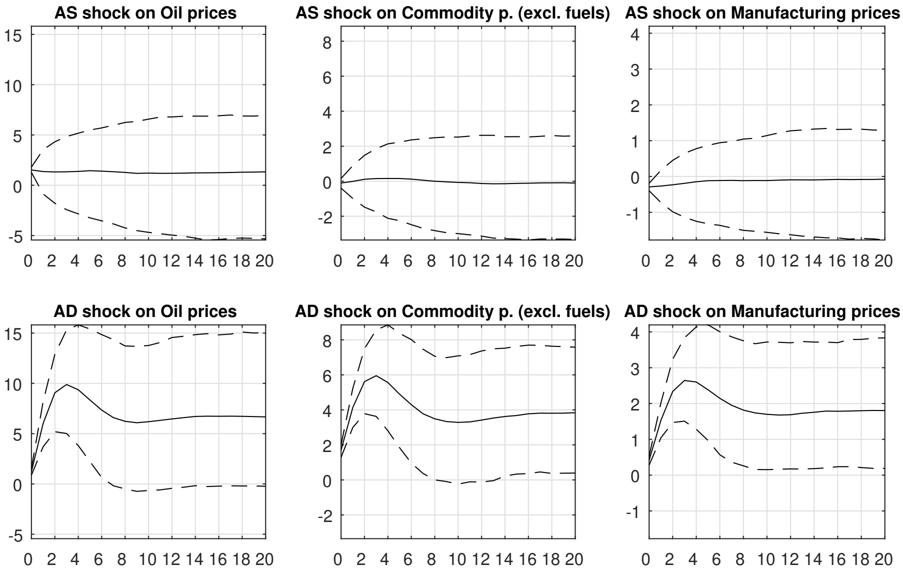
The figures 4 to 5 show how global price indicators and national consumer and producer prices outside of China react to a one standard deviation increase in the Chinese supply and demand shock. Since it is impossible to comment on the impulse response functions of all 41 countries in the data set I compute unweighted averages over countries for Europe (EU + Norway + Switzerland), North America (US and Canada), Asia (Japan, Korea, India and Indonesia) and Oceania (Australia and New Zealand).

Figure 3: Impulse response functions - Chinese variables



Notes: The panels show cumulative impulse response functions of key indicators to a Chinese AD and AS shock of one standard deviation. The impulse response functions are constructed using the "Median Target Approach" suggested by Fry et al. (2007). The dashed lines are 95 percent confidence intervals resulting from a bootstrapping and 1000 re-estimations.

Figure 4: Impulse response functions - International price indicators



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

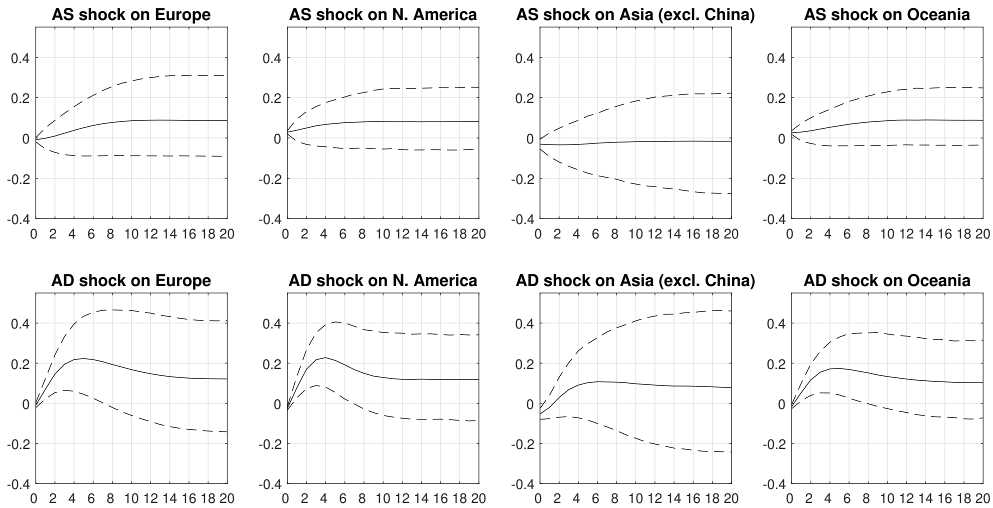
All figures show that the impulse response functions have qualitatively similar features across all price categories and country groups. On impact, most impulse responses are close to zero or insignificant, implying that spillovers from Chinese business cycle shocks are sluggish. They reach their maximum after approximately four quarters and become insignificant at large horizons, implying that the Chinese shocks do not have a long-run effect on international prices.

The impulse responses also show that the AS shock has a slightly positive but insignificant effect in all regions. This finding might be the result of two countervailing dynamics: By definition, a positive supply shock lowers inflation but raises real activity in China. Through international price competition this should also lower prices outside China. However, if higher real activity comes along with higher demand for commodities and thus raises its prices the net spillover effect of the supply shocks is unclear.

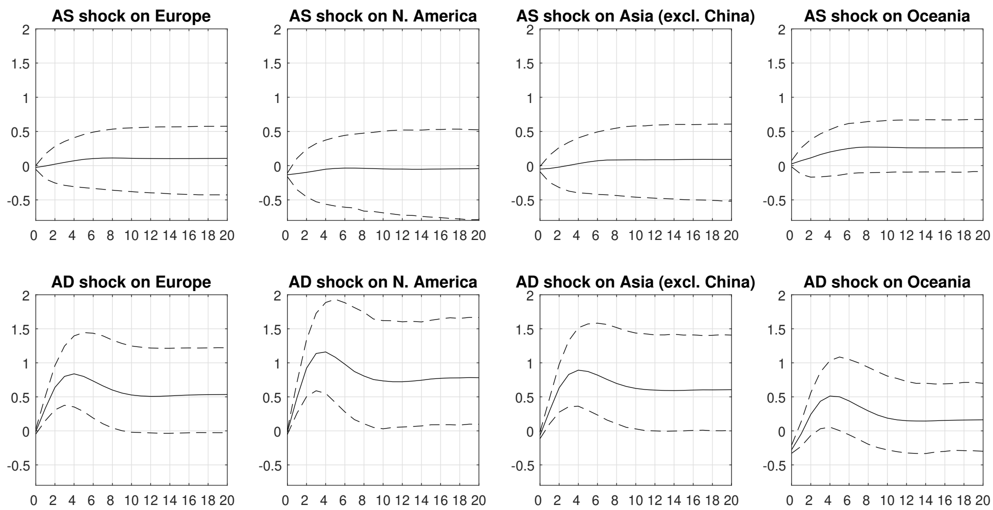
By contrast, the AD shock has a considerable and significantly positive effect on prices. This holds especially for oil and commodity prices which increase by 10 and six percent and thus can be considered as important transmission channels. The

Figure 5: Impulse response functions - National price indicators

(a) Consumer prices



(b) Producer prices



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

only exceptions are Asian consumer prices whose response functions are insignificant. One reason for this finding might be that inflation rates in Asia are more heterogenous than those in the other considered regions[7], which inflates the confidence bands around the impulse response functions. In addition, there is a large literature on the peculiarities of Japanese monetary policy which might play a role here (e.g. Ueda (2012)). In fact, if I exclude Japan from the Asia group the impulse responses of Asian consumer prices to a Chinese AD shock become positive and significant at the 32 percent level.

Producer prices react considerably stronger than consumer prices in response to a Chinese AD shock, a finding which confirms that of Eickmeier and Kühnlenz (2016). The effect is strongest in North America where producer prices increase by 1.1 percent after four quarters in response to a Chinese demand shock. In Europe, Asia and Oceania the effect amounts to 0.8, 0.8 and 0.5 percent, respectively. The most obvious reason why producer prices are more reactive to external shocks than consumer prices might be that the producer price index comprises more tradeable and manufactured goods which depend more on commodity prices. Furthermore, Bacchetta and Wincoop (2003) show that if firms operating on the consumer market are more exposed to price setting competition than importers of intermediate goods the pass-through of external shocks to consumer prices is incomplete.

5.2. Structural shock estimates

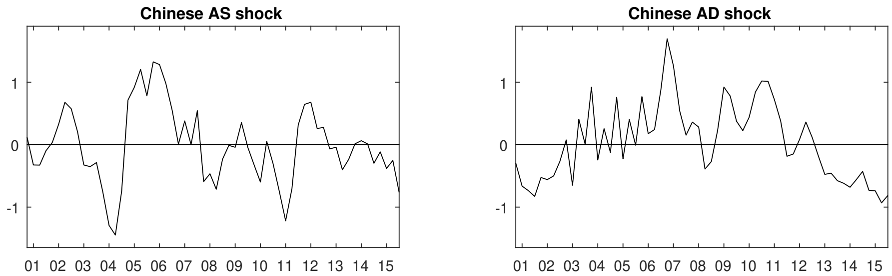
Figure 6 displays 3-quarter averages of the estimated Chinese supply and demand shock series. These series show, for each point in time, the direction of supply and demand shocks within the Chinese economy.

The Great Recession that affected China already in 2008 is driven by negative supply and demand shocks from 2007 until the second quarter of 2008. The shock magnitudes are rather moderate, which is expected since according to my model the Great recession is to a large part attributed to a fall in the international component $\hat{H}_t$. From the third quarter of 2008 until the second quarter of 2011 the demand shock becomes positive again whereas the supply shock exhibits am-

[7] Whereas in Asia the standard deviation of CPI inflation rates across countries is 0.9 percent on time-average it amounts to 0.5, 0.2 and 0.2 percent in Europe, North America and Oceania, respectively.

biguous signs until the second quarter of 2012. Afterwards both shocks become negative until the end of the sample, whereby the demand shock declines more persistently than the supply shock. Hence, China's economic slowdown can be attributed to a mixture of negative supply and demand shocks.

Figure 6: Structural shocks



Notes: The panels show 3-quarter averages of the estimated Chinese supply (AS) and demand (AD) shocks resulting from the factor-augmented vector autoregressive model with sign restrictions.

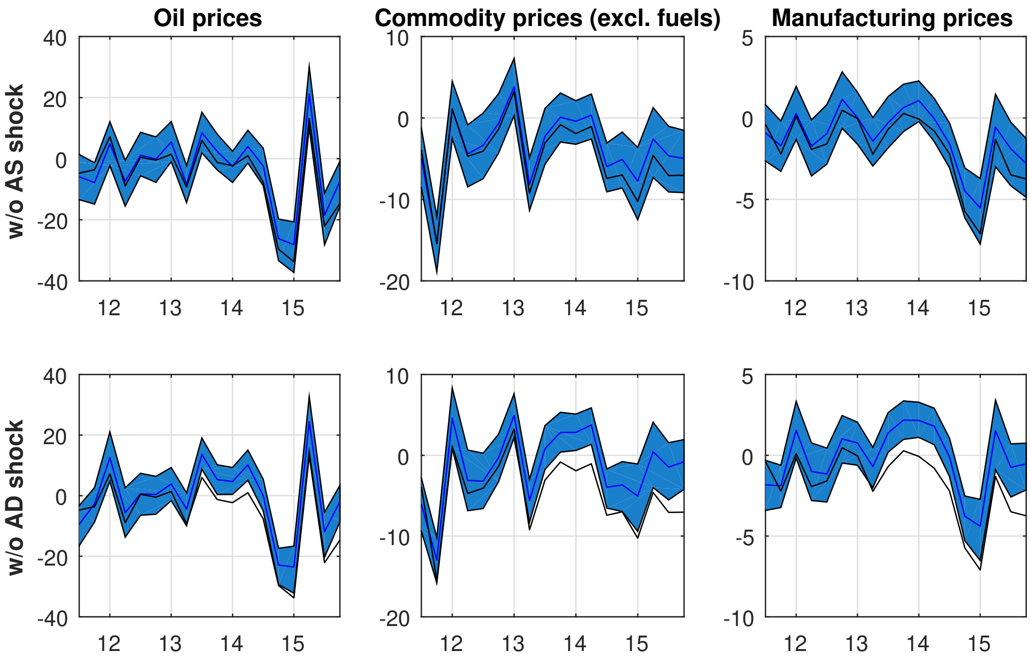
5.3. Historical decompositions

In this section I quantify by how much the Chinese economic slowdown contributed to the fall in international inflation rates from 2012 on. The historical decompositions are displayed in figures 7 and 8. Each panel shows the realized series of demeaned quarterly inflation rates (black) and a hypothetical series (blue) that results from a counterfactual analysis in which I allow for the idiosyncratic and common shocks but shut down one of the two Chinese shocks. This allows me to asses how relevant Chinese shocks are during specific historical episodes. To account for parameter uncertainty I add 95 percent confidence intervals to the hypothetical series. These confidence intervals result from bootstrapping the VAR part of the model and re-estimating it 1000 times.

The figures 7 and 8 show that the hypothetical series that result from shutting down the Chinese supply shocks are not significantly different from the realized series. The hypothetical series without the Chinese demand shock, however, are significantly and considerably higher than the realized series. This does not only hold for consumer and producer prices in almost all regions (except Asian consumer

Figure 7: Historical decompositions

International price indicators



Notes: In each panel I show the realized series of demeaned quarterly inflation rates (black) and a hypothetical series (blue) that is implied by the FAVAR. The hypothetical series results from a counterfactual analysis in which one Chinese structural shock is shut down and all other shocks are maintained. Details are given in Section 5.3. The blue shaded area around the hypothetical series are 95 percent confidence intervals resulting from a bootstrapping and 1000 re-estimations.

prices) but also for oil prices, commodity prices and manufacturing prices. In addition, I again find that producer prices react stronger to the demand shock than consumer prices do. Between 2013Q3 and 2015Q4 quarterly producer price inflation in Europe, North America, Asia and Oceania was on average 0.7, 1.0, 0.8 and 0.6 percentage points lower than the hypothetical inflation rates without the Chinese AD shock. These numbers are considerable given that the standard deviations of the quarterly inflation rates over the entire sample are 1.2, 1.8, 1.4 and 1.4 percent, respectively. In terms of consumer prices, the differences between realized and hypothetical inflation rates are slightly smaller: the average differences in Europe, North America, Asia and Oceania are on average 0.3, 0.3, 0.2 and 0.2 percentage points.

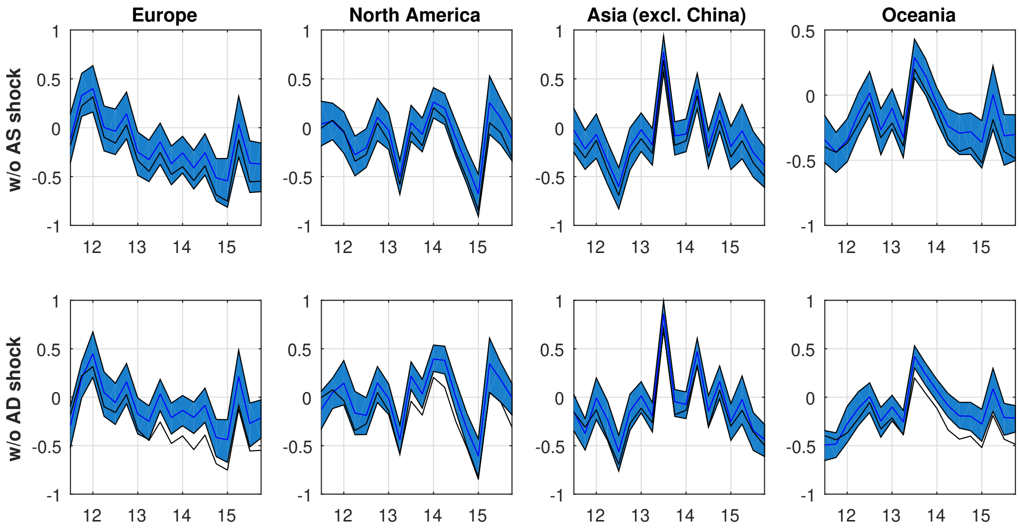
Since the sharp decline in Chinese demand from the second quarter of 2012 onwards significantly affected international inflation only by the end of 2013 it apparently took a lag of approximately one year to spill over. This finding is expected and furthermore consistent with the findings from section 5.1. By contrast, the supply shock is insignificant over the entire period. This finding might be due to the ambiguous qualitative directions of the estimated supply shock series at the end of my sample or the countervailing effects of supply shocks on international prices that I discussed in section 5.1. I conclude from these findings that the historically low inflation rates in the western economies from 2013 until 2015 can to a substantial degree be attributed to the decline in Chinese demand.

The effect of both Chinese shocks on international prices are reported in Table 3. Here I compare the realized quarterly inflation rates with hypothetical rates in which the Chinese shocks are shut down and all other shocks are maintained. I sum up all differences between these two series from Q12012 onwards, the date which I defined as the start of the Chinese slowdown. The resulting numbers are considerable, especially in terms of producer prices. Shutting down the Chinese supply and demand shocks lowers producer prices in Europe, North America, Asia and Oceania by 9.2, 12.0, 9.9 and 6.6 percent, respectively. As expected, the effects on consumer prices are lower: they amount to 3.9, 3.4, 1.8 and 3.0 percent, respectively.

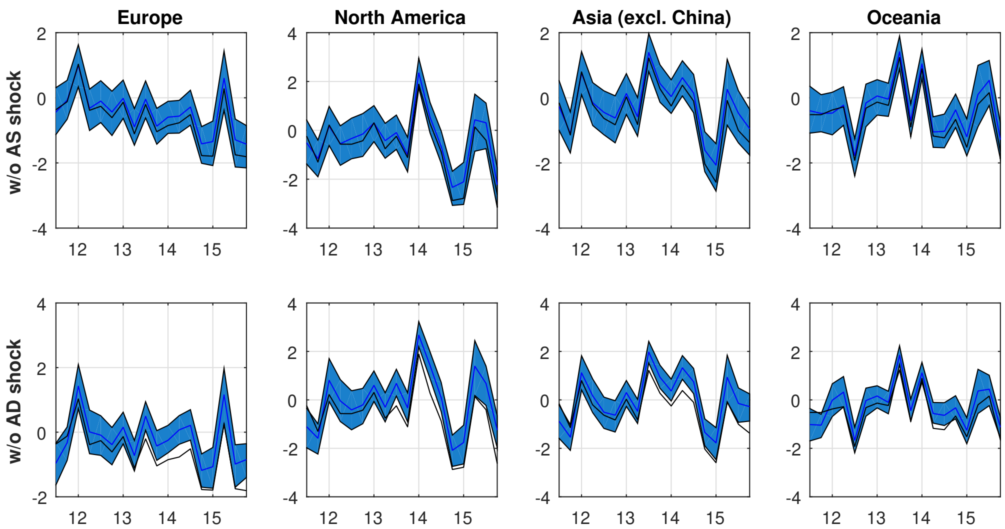
Figure 9 displays the implied price level resulting from the hypothetical quarterly inflation rates which include all shocks but the two Chinese. In addition, it shows

Figure 8: Historical decompositions - National price indicators

(a) Consumer prices



(b) Producer prices



See figure 7 for a detailed description of the graphs.

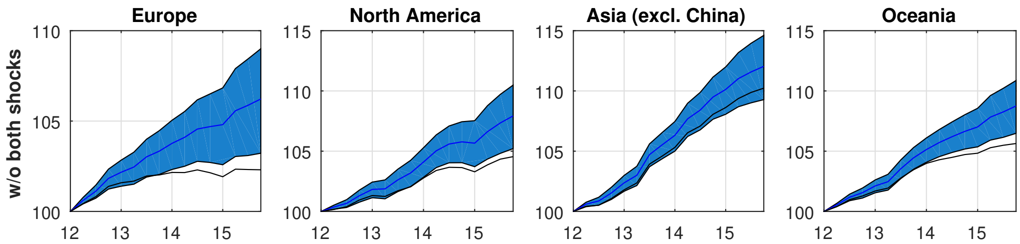
Table 3: Cumulative effects of Chinese shocks

Indicator	Europe	N. America	Asia (excl. China)	Oceania
Consumer prices	-3.9	-3.4	-1.8	-3.0
Producer prices	-9.2	-12.0	-9.9	-6.6

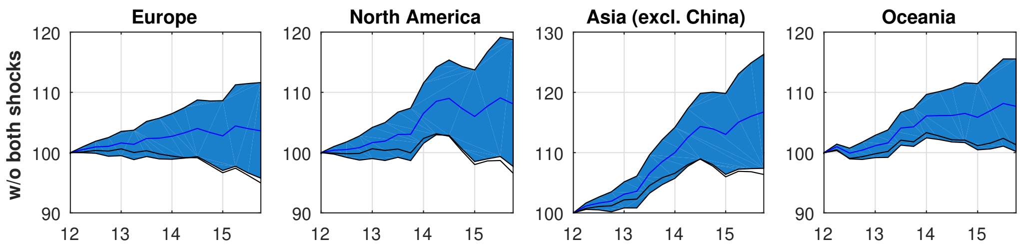
Notes: The table displays the sum of the differences between realized quarterly inflation rates and hypothetical inflation rates which result from allowing all shocks estimated from the FAVAR except the two Chinese. I sum up all differences from Q12012 until Q42015 which are significant at a 5 (10) percent level.

Figure 9: Cumulative effects of Chinese shocks

(a) Consumer prices



(b) Producer prices



Notes: In each panel I show the realized price level resulting from the quarterly inflation rates in the raw data (black) and a price level that is implied by hypothetical quarterly inflation rates (blue). These hypothetical inflation rates result from a counterfactual analysis in which both Chinese structural shocks of the FAVAR are shut down and all other shocks are maintained. Details are given in Section 5.3. The price levels are normalized to 100 in the base period 2012:Q1.

the realized quarterly inflation rates resulting from the raw data. I find that between 2012 and 2015 the Chinese influence has significantly lowered prices in almost all cases. In Europe and North America, the effect was strong enough to turn the positive dynamics in the hypothetical price level into negative. Put differently, whereas the realized producer prices dropped by 5.0 percent in Europe and by 3.4 percent in North America, the counterfactual prices without the Chinese economic slowdown would have increased by 3.5 and 8.0 percent, respectively.

5.4. Robustness checks

As customary in empirical papers, I perform several sensitivity checks to the baseline model to strengthen the credibility of my results. In the following subsections, I modify the baseline FAVAR as described and re-estimate it then, leaving all other settings unchanged. The sensitivity of the results is analyzed on the basis of the cumulative slowdown effect reported in Table 3.

5.4.1. Ordering of variables

For orthogonalizing the VAR residuals in the baseline setting I set the Chinese variables below the international factors. Hence, I assume that the international factors react to Chinese shocks only with a delay of one quarter whereas the Chinese variables react immediately to international shocks. In a first experiment, I check if this ordering plays a role for my results and conclusions. I re-estimate the VAR setting the Chinese variables above the international factors and again compute the cumulative effects of shutting down the Chinese shocks on international prices. The results are reported in the second line of Table 4, together with the baseline results. As it turns out, the cumulative effects of the Chinese slowdown are barely distinguishable from those of the baseline and therefore my main conclusions remain valid.

5.4.2. Long-run restrictions

In the next step, I check if my results hinge on the sign restrictions which are imposed on the orthogonalized VAR residuals. In section 4 I described and justified two short-run sign restrictions to identify an aggregate Chinese demand and supply shock. However, Blanchard and Quah (1989) argued that supply and demand shocks can be distinguished through their long-run effects on GDP and prices. Therefore I re-estimated the model using their identification scheme. I assume that the demand shock has zero long-run effect on Chinese GDP whereas the effect of the supply shock is completely unrestricted. The results are displayed in row three of Table 4. Again, the effects of the Chinese shocks on international inflation are very similar to those of the baseline model. However, a few changes are worth mentioning. As opposed to the usual pattern, the unrestricted (supply) shock drives Chinese GDP growth and inflation in the same direction. Hence, the only difference between the impulse responses of both shocks are that the long-run effect of the restricted (demand) shock on Chinese GDP is zero. Accordingly, international prices react positively and significantly to both shocks, which is at odds with theory and my findings in section 5.1. The historical decompositions therefore would indicate that the Chinese slowdown has lowered international inflation both through supply and demand effects. However, due to the unreasonable impulse response functions of the supply shock I consider the identification through long-run restrictions as too weak.

5.4.3. Control for oil prices

This part deals with 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) about half of this decline can be attributed to a slowdown in global real activity whereas about one third was due to oil supply shocks. Whereas I already control for the drop in real activity through the factors $\hat{H}_t$ I need to rule out the risk that oil supply shocks are confused with Chinese supply shocks since both shocks are expected to have opposite effects on Chinese GDP and inflation. In order to control for the oil supply shocks I replace the factor space by $F_t = [\hat{H}_t' \quad \Delta cgdp_t' \quad \Delta cdefl_t' \quad \Delta oilp_t']'$ 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 fourth row of Table 4. Controlling for oil price shocks apparently slightly lowers the total effect of China's slowdown on international inflation in all regions. This finding is to a considerable degree due to the third and fourth quarters of 2014, in which the oil price drop occurred.

Table 4: Robustness checks

	Europe	North America	Asia (excl. China)	Oceania
		Consumer prices		
Baseline	-3.9	-3.4	-1.8	-3.0
Ordering of variables	-3.8	-3.0	-2.1	-2.9
Long-run restrictions	-4.0	-3.4	-1.9	-3.1
Control for oil prices	-3.6	-2.5	-1.7	-2.7
Control for Euro crisis	-3.8	-3.3	-2.0	-2.9
Number of factors	-3.7	-3.0	-1.7	-2.7
Regional factors	-3.9	-2.2	-1.6	-2.6
VAR(4)	-3.9	-3.4	-1.7	-3.1
		Producer prices		
Baseline	-9.2	-12.0	-9.9	-6.6
Ordering of variables	-8.3	-10.3	-9.1	-7.0
Long-run restrictions	-9.2	-12.0	-9.9	-6.6
Control for oil prices	-7.6	-9.4	-7.7	-5.0
Control for Euro crisis	-8.7	-11.0	-9.4	-6.6
Number of factors	-7.8	-9.7	-7.4	-5.2
Regional factors	-7.8	-8.6	-7.8	-4.7
VAR(4)	-8.1	-11.4	-8.7	-4.8

Notes: The table displays the sum of the differences between realized quarterly inflation rates and hypothetical inflation rates which result from allowing all shocks estimated from the FAVAR except the two Chinese. I sum up all differences from Q12012 until Q42015.

However, the total effects are still similar to those in the baseline setup and therefore do not affect my conclusions. Furthermore, it should be taken into account that holding oil prices constant in the estimation rules out an important transmission channel of Chinese business cycle shocks and these numbers therefore rather underestimate the slowdown effect.

5.4.4. Control for Euro crisis

I also address the possibility that the global factors $\hat{H}_t$ are not sufficient to control for the Euro crisis, which kicked in between 2012 and 2013 in terms of European GDP and thus occurred at the same time as the Chinese economic slowdown. To account for that issue I add Italian real GDP growth $\Delta itagdp_t$ as a slow-moving variable to the factor space ($F_t = [\hat{H}_t' \quad \Delta itagdp_t' \quad \Delta cgdp_t' \quad \Delta cdefl_t']'$) 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. However, re-running the estimation based on this specification yields only negligible changes (see row five of Table 4).

5.4.5. Number of factors

It might be argued that four common factors do not sufficiently represent X_t and thereby fully control for the international business cycle in the VAR. Since the $IC3$, the $PC1$ and the $PC2$ proposed by Bai and Ng (2002) suggest five factors I re-estimate the model using the first five principal components of X_t in the VAR instead of four, leaving everything else equal. It turns out, however, that the Chinese slowdown effect on international inflation (row six in Table 4) are very similar to the baseline model.

5.4.6. Regional factors

It is a popular narrative in the literature that regional factors dominate 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 10 regional factors, namely four for both Europe and North America and two for Asia (excluding China). The factors are estimated by extracting principal components from the region-specific subsamples of X_t[8]. Then I define the factor space F_t as $F_t = [\hat{H}_t^{EU'} \quad \hat{H}_t^{NA'} \quad \hat{H}_t^{AS'} \quad \Delta cgdp_t' \quad \Delta cdefl_t']'$ and re-estimate the FAVAR. Since the ordering of the regional factors is arbitrary, I

[8]The number of factors is determined by the IC2 criterion by Bai and Ng (2002), which points to 4 factors for North America and Europe and 2 factors for Asia (excluding China). I cleaned the regional factors from the Chinese component using the procedure in section 4 and the regression equation 4

tried different ones but the results are barely distinguishable from those presented here. The cumulative effects of the Chinese shocks in the historical decomposition are reported in line seven of Table 4. Again, the numbers are very similar to those of the baseline estimation and only in a few cases slightly smaller.

5.4.7. Lag order

Finally, I checked if a higher lag order in the VAR changes my results. Since the AIC suggests the highest possible lag order I estimated the model with four lags to keep the model estimable. I find that both the impulse responses and the structural shock estimates are very similar to those in the VAR(1) of the baseline setup. The same holds for the cumulative effects of the Chinese slowdown, which are reported in line eight of Table 4. In case of consumer prices, they are almost identical to those of the VAR(1). The effects on producer prices are slightly smaller but are still of the same magnitude, so my conclusions are not affected.

6. Conclusion

I have fit a factor-augmented vector autoregressive model to a large-dimensional macroeconomic dataset covering 41 countries over the period 2000-2015 to examine the role of the Chinese economic slowdown for international inflation dynamics. I have identified and estimated Chinese supply and demand shocks and investigated the impulse responses of consumer and producer prices in North America, Europe, Asia and Oceania to these shocks. Furthermore I carried out historical decompositions of these variables to account for the role of the recent Chinese economic slowdown. My main findings are: (i) Impulse response analyses indicate that Chinese business cycle shocks and especially demand shocks significantly spill over to inflation rates in Europe, North America, Asia and Oceania, mainly transmitted through global oil, commodity and manufacturing prices. (ii) The Chinese growth slowdown that started in 2012 can be attributed to a fall in aggregate Chinese demand and supply. (iii) Historical decompositions indicate that the fall in Chinese demand lowered national prices in Europe, North America, Asia and Oceania by up to 12 percent from the third quarter of 2013 on.

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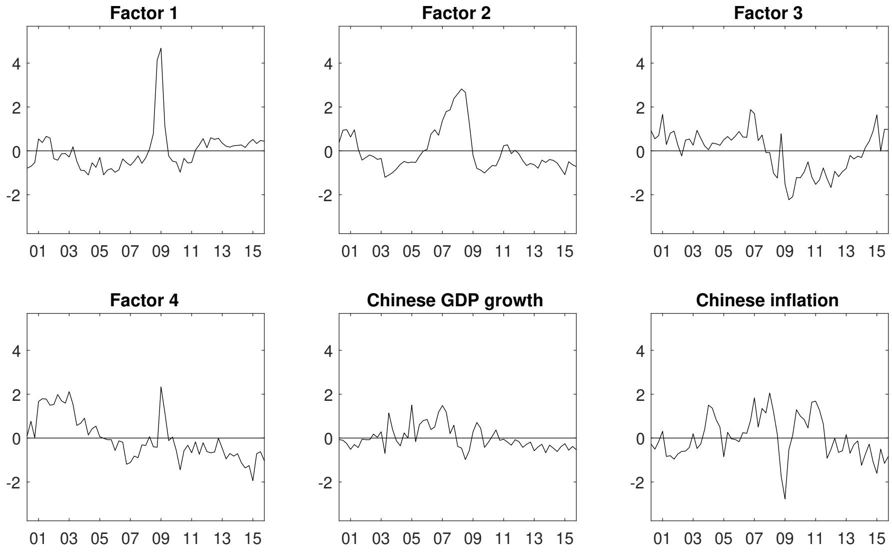
Appendix A. Additional Figures and Tables

Figure A.10: Factors



Notes: The panels show the estimated factors and observables used in the FAVAR.

Table A.5: Forecast error variance decomposition of Chinese variables

Country group	h	International factors	Chinese supply	Chinese demand	Idiosyncratic
GDP growth	2	19.3	25.0	55.7	0
	8	20.4	24.5	55.1	0
GDP deflator growth	2	27.1	31.2	41.7	0
	8	34.5	25.3	40.3	0
CPI inflation	2	15.3	10.6	19.5	54.6
	8	19.5	9.6	21.5	49.4
Export growth	2	21.8	2.3	8.2	67.7
	8	35.4	1.9	13.0	49.7
Import growth	2	18.8	0.1	4.0	77.1
	8	26.6	0.2	7.8	65.4
Employment growth	2	27.0	1.8	2.8	68.4
	8	30.7	3.8	4.2	61.3

Notes: The table shows the percentage decomposition of the forecast error variance of inflation and into factors, Chinese demand and supply shocks and own shocks. h dentotes the forecast horizon.

Table A.6: Forecast error variance decomposition of international price indices

Country group	h	International factors	Chinese supply	Chinese demand	Idiosyncratic
Oil prices	2	49.5	1.3	17.8	31.4
	8	52.2	1.2	18.2	28.4
Commodity p. (excl. fuels)	2	25.9	0.1	27.8	46.3
	8	33.7	0.1	27.0	39.2
Manufacturing prices	2	42.1	1.2	27.6	29.2
	8	46.7	1.1	27.1	25.1

Notes: The table shows the percentage decomposition of the forecast error variance of inflation and into factors, Chinese demand and supply shocks and own shocks. h dentotes the forecast horizon.

Table A.7: Forecast error variance decomposition of CPI inflation

Country group	h	International factors	Chinese supply	Chinese demand	Idiosyncratic
Europe	2	31.1	0.7	8.8	59.3
	8	33.6	1.3	10.1	55.0
North America	2	34.8	0.5	11.2	53.5
	8	37.5	0.6	12.1	49.8
Asia (excl. China)	2	18.0	1.3	5.7	75.1
	8	19.5	1.6	6.4	72.4
Oceania	2	22.0	0.4	6.2	71.4
	8	23.4	0.6	6.8	69.1

Notes: The table shows the percentage decomposition of the forecast error variance of inflation and into factors, Chinese demand and supply shocks and own shocks. h dentotes the forecast horizon.

Table A.8: Forecast error variance decomposition of PPI inflation

Country group	h	International factors	Chinese supply	Chinese demand	Idiosyncratic
Europe	2	32.7	1.4	13.1	52.8
	8	35.7	1.6	14.4	48.3
North America	2	32.3	0.6	13.8	53.3
	8	35.2	0.6	14.9	49.3
Asia (excl. China)	2	33.0	2.1	12.1	52.8
	8	35.0	2.1	13.8	49.1
Oceania	2	37.8	0.3	10.5	51.4
	8	40.0	0.5	12.5	46.9

Notes: The table shows the percentage decomposition of the forecast error variance of inflation and into factors, Chinese demand and supply shocks and own shocks. h dentotes the forecast horizon.