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Abstract

Since the 1980's China has experienced very high economic growth and its share in global trade has increased rapidly. Nowadays, however, the Chinese economy is rebalancing and its growth is slowing. The paper investigates the spillover effects of a negative demand shock and negative stock price shock in the Chinese economy on other countries. We apply a GVAR model, that enables us to model international linkages between countries. Our results show that a one percent negative China GDP shock reduces global growth by 0.22% in the short run. We find that GDP shock affects emerging economies more strongly than advanced economies. We also show that stock prices shock affects only emerging economies and does not affect advanced economies.

JEL codes: C32, E32, F10, O53

Keywords: global VAR, China's slowdown, spillovers

1. Introduction

Over the last decades China has become the main engine of world economic growth. The rapid growth in China was possible due to the country's joining the World Trade Organization in 2001, trade liberalization and high growth of investment in the domestic economy. China's share in world trade increased from about 2.6% in 1993 to about 12.3% in 2015.[1] Currently, however, China's export-led growth model is maturing and the growth of real GDP is slowing. The Chinese economy is slowly rebalancing, meaning that the share of consumption to GDP is increasing and the share of investment to GDP is decreasing (see Zhang, 2016).

Given the emergence of the Chinese economy as a global force in the world economy, it is not surprising that, recently, much attention of researchers has been directed to the international spillover effects of China's slowdown. The research was intensified in the second half of 2015, when increased volatility in the Chinese stock exchange, coupled with a yuan devaluation, largely affected global financial markets.

The article examines the role of China in the world economy. The aim of the paper is to evaluate the impact of shocks emanating from the Chinese economy on other economies. We concentrate on two possible shocks to Chinese economy, one being a negative demand shock, and the other being a negative stock price shock. We compare the response of advanced as well as emerging and developing economies. We show that shocks that originate in China translate to the majority of countries in the global economy in a statistically significant way, having the strongest impact on emerging market economies – particularly commodity exporters and other Asian economies. Additionally we show, how the two shocks are transmitted to China's domestic economy.

[1] China is the largest exporter in the world (the value of exports in 2015 was 2,275 billion dollars, that is more than 13% of global export) and the second largest importer of the world (the value of imports in 2015 was 1,682 billion dollars, that is almost 10% of global import), (see World Trade Statistical Review 2016, WTO).

China plays an important role both in traditional global trade and in the global supply chains, processing intermediate goods and re-exporting them to other regions. Therefore for some countries, the direct effects of slowdown in the Chinese economy might be small, whereas the indirect effects, especially through the neighbour countries, might be significant.

High investment in the domestic economy and an ongoing urbanization process in China have caused an increase in Chinese demand for metals.[2] Because of high metal consumption and high oil consumption, China's slowdown may cause large changes in the prices of commodities. Thus, it indirectly affects all commodity exporters, even though they do not trade much with China directly.

The regional impact of China on the Asia-Pacific region should also be taken into account. Since 2008, because of the recession and anemic growth in the United States and the euro zone, advanced economies demand for Asia-Pacific exports has been decreasing. However, Asia-Pacific countries have benefited from the surging Chinese domestic demand. Over the last five years the export from Asia-Pacific countries to China have doubled. China has become the largest market for Asian economies, surpassing Japan in 2005 and United States in 2007 (Inoue et al., 2015). Because China is a central point of the Asian supply chains, the slowdown of the Chinese economy is particularly troubling for Asia-Pacific countries.

Moreover, a sudden or stronger than expected slowdown in the Chinese economy may increase uncertainty in global financial markets and it may cause the depreciation of the Chinese renminbi. Recent events have shown that turbulences in China's financial market cause capital outflows from emerging markets and depreciation of their currencies.

The tool that enables concise analysis of the world economy is the global vector autoregressive model (GVAR). The GVAR models are popular in recent foreign literature. The GVAR models have a number of applications in modern

[2] About 54% of global iron ore consumption and about 41% of global copper consumption belong to China. China represents about 11% of global oil consumption, that is related to increase in domestic consumption and development of automobile sector (see Gauvin and Rebillard, 2015).

macroeconomics, they are attractive tool to study spillover effects, for example, Georgiadis (2015a) analyses the impact of the common euro area monetary policy on individual euro area economies, Backé et al. (2013) examine the impact of the euro area shocks on Central, Eastern, and Southern Europe, Feldkircher (2015) investigates the impact of foreign shocks on emerging Europe and Georgiadis (2015b) analyses the impact of the US shocks on other economies. Whereas Chen et al. (2010), Ahuja and Myrvoda (2012), Ahuja and Nabar (2012), Duval et al. (2014), Feldkircher and Korhonen (2014), Inoue et al. (2015), Cashin et al. (2016) apply the GVAR models to study spillover effects from China's economy.

There are a number of differences between our GVAR model and other research on spillovers from China. One of the most important being the usage of novel data set. The differences concern, for instance, the choice of variables (no long term interest rate is used in our model), the choice of countries and regions, and the time span of data.

The structure of the paper is following. Section 2 contains a literature review. Section 3 describes the GVAR methodology. Section 4 presents the data. Section 5 presents the results, that is the implications of a negative GDP shock in China and the implications of negative equity price shock in China. The last section concludes.

2. Literature review

The GVAR models are frequently used to assess the impact of one big economy on other smaller economies and on the whole global economy. Below we describe the chosen papers that concentrate on China (**Cashin et al. (2016), Inoue et al. (2015), Feldkircher and Korhonen (2014), Cesa-Bianchi et. al (2012)**), the United States (**Georgiadis (2015b)**), or the euro area (**Backé et al. (2013), Georgiadis (2015a)**).

In the most recent IMF paper **Cashin et al. (2016)** investigate the impact of China's slowdown and the higher global financial market volatility on other economies. The authors estimate the GVAR model that consists of 26 VARX* models, among them the euro area and 25 single economies. The results indicate that the negative output shock in China has the largest effect on less-diversified commodity exporters and ASEAN-5 countries (Indonesia, Malaysia, Singapore, Thailand, without Philippines). The results suggest that following 1% decrease of the real GDP growth in China, the global growth decreases by 0.23% in a short term, and oil prices fall by 2.8% in a long term. Cashin et al. (2016) estimate the model with foreign variables constructed using time-varying trade weights, which allows to see how the global impact of the Chinese negative output shock has changed in time. Not surprisingly, the impulse responses based on the weights in the 1980s and in most cases in the 1990s are not statistically significant, whereas the impulse responses based on the weights in the 2000s are statistically highly significant and are also larger. It shows the evolution of trade between China and other countries and its emergence as a global economic power.

There is a number of similar IMF papers that, using the GVAR models, investigate the role of the Chinese economy in the global economy (see **Ahuja and Myrvoda 2012, Ahuja and Nabar 2012, Chen et al. 2010, Duval et al. 2014**). The papers concentrate on different aspects of the spillover effects. **Chen et al. (2010)**, for instance, show how deteriorating the quality of credits to firms and deteriorating banks' balance sheets in China negatively affect the rest of world.

Inoue et al. (2015) analyse the spillover effects from Chinese economy to Asia-Pacific countries. The sample contains 33 countries between 1979Q1 and 2014Q3. The results suggest that China's slowdown affects, to the greatest extent, commodity exporters, such as Indonesia, and countries that largely depend on exports – Japan, Malaysia, Singapore and Thailand. Thus, the conclusions are similar to Cashin et al. (2016). The study shows that the negative output shock in China has a negative impact on oil crude prices, metal prices as well as agricultural products prices.

Feldkircher and Korhonen (2014) apply the GVAR model to assess the influence of China's economy on emerging market economies, especially the emerging market economies in Europe. The sample includes 52 countries and the spans from 1995Q1 to 2011Q4.The results show that 1% output increase in China translates into 1.2% permanent increase in output in China and 0.1%-0.5% increase in real GDPs in large advanced economies. The output increase causes 0.2% rise in real GDP in Central-Eastern Europe and in the former Commonwealth of Independent States and 0.1% fall in real GDP in South-Eastern Europe. The authors also consider the impact of 50% increase in oil prices on China and other emerging economies. As a consequence of this shock one may observe 6% increase in real GDP in Russia, which is one of the biggest oil exporters, and 4.5% decrease in real GDP in China in a long term. Moreover, Feldkircher and Korhonen assess the effect of the Chinese renminbi revaluation. It turns out that 10% appreciation of renminbi against euro implies 0.4% increase of real GDP in the euro area and an analogous decrease in real GDP in China.

Backé et al. (2013), using the GVAR model, examine economic spillovers from the euro area to Central, Eastern, and Southern Europe between 1995Q1 and 2011Q4. The authors try to determine and compare the power of both financial and trade channel. The results show that the kind of a trade channel is more significant for South-Eastern Europe, and less significant for Russia and the CIS countries. Both channels have the same impact on Central Europe. According to the obtained results, the combined effect of the two channels, that is 1% long-term increase in

output in the euro area, causes 0.3% increase in output in Central Europe and Russia, and 0.7% increase in output in the CIS countries.

Georgiadis (2015a) studies the transmission of the common euro area monetary policy across the individual euro area economies. The author estimates the GVAR model and identifies monetary policy shocks by sign restrictions. The differences within the monetary transmission mechanism in the euro area countries seem to depend on the differences in the structural characteristics of the economies. The euro area countries in which a share of sectors with the demand sensitive to interest rate changes in the accumulated industry is bigger exhibit stronger monetary transmission to real economic activity. Similarly, stronger transmission is observed in the countries with more real wages rigidities and/or fewer unemployment rigidities.

In his second paper, **Georgiadis (2015b)** studies spillover effects from the US economy. The study, similarly to the previous paper, concerns 61 countries from 1999Q1 to 2009Q4. The author tries to find out which structural features of the economies determine the US spillover effects. The results of the study suggest that policymakers could mitigate the US spillover effects by encouraging trade integration, financial market development, flexibility of exchange rates and by reducing labour market rigidities. On the other hand, other policies, such as slowing the process of the financial integration and industrialisation or participation in the global value chains, could also reduce the spillover effects, but would probably decrease the level of long-run economic growth as well.

Cesa-Bianchi et. al (2012), interestingly, conduct a set of counter-factual simulations – they keep constant the parameters of VARX* models and solve the GVAR with four different sets of trade matrixes – they assume fix trade weights for 1985, 1995, 2005 and 2009. By doing so they test how changed trade patterns altered transmission of international business cycle to Latin America and the world economy. They include 25 countries plus the euro area from 1979Q2 to 2009Q4. The study concentrates on 5 Latin American countries: Argentina, Brazil, Chile, Mexico and Peru. They show that the impact of China GDP shock on the Latin

American economies increased by three times since the mid-1990s, while the impact of US GDP declined by half. The dependence of Latin America on China economy seems to be one of the main reasons why Latin America economies recovered much faster than initially anticipated from the global financial crisis.

3. Research methodology

The global vector autoregressive model (GVAR) is a concise model of the whole global economy that captures economic and financial linkages between countries. It enables to produce both the impulse responses of domestic economies or regions and the responses of the whole economy.

Global vector autoregressive model was originally proposed by Pesaran et al. (2004) and further developed by Dees et al. (2007). This approach has been used to investigate a number of different problems (see for instance Cesa-Bianchi et. al (2012), note 2).

Dees et al. (2007) present a theoretical framework for GVAR analysis. They develop bootstrap procedures for the GVAR estimation used, for example, to test structural stability of the parameters and to establish confidence bands for impulse responses. They use both generalized and structural impulse responses.

We build and estimate a GVAR model using the modified GVAR Toolbox 2.0, which contains necessary procedures in Matlab and a user friendly interface in Excel (see Smith and Galesi, 2014).

Estimation of the GVAR model is a two-step procedure. Firstly, one estimates small VARX models for each country that are conditional on the rest of world. The country specific models comprise domestic, foreign and optionally global variables or dominant unit variables. The foreign variables are weakly exogenous variables that are constructed as cross-country weighted averages. The global variables may be deterministic and not determined within the model or modelled as dominant unit. The dominant unit means a dominant player in the global economy, and acts as a dynamic factor in the regressions of the non-dominant units. Secondly, using the spillover matrix, one links individual countries' models into one global VAR model.

For simplicity, below we present the GVAR model equations without dominant unit. The dominant unit is estimated as VAR model with lagged feedback variables (meaning foreign variables in the GVAR model). When modelling the GVAR with

dominant unit, one needs to add components of dominant unit to all equations. When solving the model, the dominant unit variables are treated similarly to foreign variables (see Smith and Galesi, 2014, p.152).

In the following model we consider N countries. For a particular country i we define the following VARX*(P,R) model:

$$x_{it} = \alpha_{i0} + \alpha_{it}t + \sum_{p=1}^{Pi} \Phi_{ip} x_{i,t-p} + \sum_{r=0}^{Ri} \Lambda_{ir} x^*_{i,t-r} + u_{it}, \qquad (1)$$

where $x_{i,t}$ is a vector $1 \times k_i$ of domestic variables, $x^*_{i,t}$ is a vector $1 \times k^*_i$ of foreign variables, $x^*_{it} = \sum_{j=0}^{N} \omega_{ij} x_{jt}$, $\omega_{ii} = 0$, ω_{ij} are weights that are calculated on the basis of bilateral trade or financial flows matrix, $\sum_{j=0}^{N} \omega_{ij} = 1$;

ω_{ij} are u_{it} weakly correlated $\sum_{j=0}^{N} \omega_{ij} u_{jt} \xrightarrow{p} 0$ when $N \to \infty$.

GVAR models allow to distinguish regions (for example Central-Eastern Europe or the euro area). Then the regional variables are calculated as the cross-sectional weighted averages of respective variables for individual countries. The Purchasing Power Parity GDP weights are used to aggregate the domestic variables.

The model can be written in the error correction form:

$$\Delta x_{it} = \mu_i + \sum_{j=1}^{r_i} \gamma_{ij} ECT_{ij,t-1} + \sum_{p=1}^{P} \widetilde{\Phi}_{ip} \Delta x_{i,t-p} + \sum_{r=0}^{R} \widetilde{\Lambda}_{ir} \Delta x^*_{i,t-r} + e_{it},$$

where r_i is a number of cointegrating relations.

We define a vector $z_{it} = \begin{pmatrix} x_{it} \\ x^*_{it} \end{pmatrix}$ that, for a given country, contains its domestic variables and the foreign variables as well. We write:

$$A_{i0} z_{it} = a_{i0} + a_{i1} t + A_{i1} z_{i,t-1} + \cdots + A_{ip} z_{i,t-Pi} + u_{it},$$

where $A_{i0} = \left(I_{k_i}, -\Lambda_{i0}\right)$, $A_{ij} = \left(\Phi_{ij}, \Lambda_{ij}\right)$ $j = 1, \ldots \max(P_i, R_i)$, $\Phi_{ij} = 0$ for $j > P_i$ and $\Lambda_{ij} = 0$ for $j > R_i$, $z_{it} = W_i x_t$, where W_i are $(k_i + k^*_i) \times k$ $(k = \sum_{i=0}^{N} k_i)$

link matrixes, that are calculated on the basis of trade flows and $x_t = (x'_{0t}, x'_{1t}, \dots, x'_{Nt})'$. Further the model can be written as:

$$A_{i0}W_i x_t = a_{i0} + a_{i1}t + A_{i1}W_i x_{t-1} + \cdots + A_{ipi}W_i x_{t-pi} + u_{it},$$

Next, by stacking the individual country models, we obtain the global VAR model in domestic variables only:

$$G_0 x_t = a_0 + a_1 t + G_1 x_{t-1} + \cdots + G_p x_{t-p} + u_t, \tag{2}$$

$$G_0 = \begin{pmatrix} A_{00}W_0 \\ A_{10}W_1 \\ \dots \\ A_{N0}W_N \end{pmatrix}, G_j = \begin{pmatrix} A_{0j}W_0 \\ A_{1j}W_1 \\ \dots \\ A_{Nj}W_N \end{pmatrix}, a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \dots \\ a_{N0} \end{pmatrix}, a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \dots \\ a_{N1} \end{pmatrix}, u_t = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \dots \\ u_{Nt} \end{pmatrix}.$$

The $G_0$is known (from estimation of individual country models), we thus multiply both sides of equation (2) by G_0^{-1} and we get the GVAR(P) model:

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + \cdots + F_p x_{t-P} + \varepsilon_t, \tag{3}$$

where $b_0 = G_0^{-1}a_0,\ b_1 = G_0^{-1}a_1, F_j = G_0^{-1}G_j\ j = 1, \dots, p, \varepsilon_t = G_0^{-1}u_t$. Equation (3) is solved recursively.

After estimating the GVAR model, generalized impulse response functions (GIRF) are calculated. Because of a large number of variables, it is difficult to use standard impulse response functions that assume orthogonal shocks (see Sims, 1980). GIRF were introduced by Koop, Pesaran and Potter in 1996 (see Koop et al. 2006). It is important to note that the shape of GIRF does not depend on the ordering of the variables. GIRF may be represented by the following equation:

$$GIRF(x_t, n, \varepsilon_{jlt}) = E\left[x_{t+n} | \varepsilon_{jlt} = \sqrt{\sigma_{jj,ll}}, I_{t-1}\right] - E[x_{t+n} | I_{t-1}]. \tag{4}$$

where I_{t-1} is an information set at time $t-1$, $\sigma_{jj,ll}$ is the diagonal element of the variance-covariance matrix Σ_ε corresponding to the lth equation in the jth country and n is the horizon. It appears that on the assumption that $\boldsymbol{\varepsilon}_t$ has a multivariate normal distribution, the GIRFs of a one standard error shock at time t to the lth equation on the ith variable at time t+n is given by the ith element of:

$$GIRF(x_t, n, \varepsilon_{lt}) = \frac{e_l' \boldsymbol{A}_n G_0^{-1} \Sigma_u e_l}{\sqrt{e_l' \Sigma_u e_l}}, n = 0,1,2, \dots, l, j = 1,2, \dots, k, \tag{5}$$

$\boldsymbol{A}_n$ is a matrix obtained from moving average representation of equation 3:

$$x_t = d_t + \sum_{s=0}^{\infty} \boldsymbol{A}_s \varepsilon_{t-s}, \tag{6}$$

and $e_l = (0,0, \dots ,1,0, \dots ,0)'$ is a selection vector with unity as the lth element.

4. Data

When deciding on the choice of countries, in the first step we take all countries that are included in the BIS effective exchange rate (EER) indices – 60 economies plus euro area (broad weights). However, we end up with 55 economies, because we notice that including Algeria, Chinese Taipei, Malta, United Arab Emirates, Venezuela makes the model unstable – it is probably due to low quality of data for these countries.

The chosen economies together cover more than 90% of the global GDP. The euro area countries are grouped into euro area region. Table 1 presents the geographical scope of analysis.

Table 1. Countries and regions included in the GVAR model

euro area	Argentina	Korea
Austria	Australia	Malaysia
Belgium	Brazil	Mexico
Cyprus	Bulgaria	New Zealand
Estonia	Canada	Norway
Finland	Chile	Peru
France	China	Philippines
Germany	Colombia	Poland
Greece	Croatia	Romania
Ireland	Czech Republic	Russia
Italy	Denmark	Saudi Arabia
Latvia	Euro	Singapore
Lithuania	Hong Kong	South Africa
Luxembourg	Hungary	Sweden
Netherlands	Iceland	Switzerland
Portugal	India	Thailand
Slovakia	Indonesia	Turkey

Slovenia	Israel	United Kingdom
Spain	Japan	United States

Authors often use updated versions of Pesaran et al. (2004) dataset: Dees et al. (2007) present a model for 26 countries over the period 1979-2003, or Cesa-Bianchi et al. (2012) use very similar dataset for the same countries over 1979-2006. Many other studies use their datasets, that are publicly available (see Dreger and Zhang 2014). Some authors extend up and revise the data file forward (Bettendorf 2017, Cashin et al. 2016, Inoue et. al 2015).

In contrast, we build our dataset from scratch. Our dataset is new and was not previously used in any study. Also the choice of variables in our study is different.

Below we present data used in the project. We test the robustness of the results with respect to different combinations of data. We use quarterly observations.[3] We collect data from 1995Q1 to 2016Q3. The inclusion of emerging market economies limits the time span of the analysis, thus, it is difficult to start our sample earlier. It is worth mentioning, that the GVAR model allows for omitting some time series (for example GDP for Algeria) - but it is not possible to include a time series with some missing data (for example for the second quarter of 2013).

The main data used in the model are: real GDP, price level (CPI), stock market index, real effective exchange rate (REER), and short term interest rate.

Real GDP and CPI are 2010 indices (2010=100). The data are seasonally adjusted. The source of these data is Thomson Reuters Datastream. The variables are in logarithms.

Short term interest rate is IMF International Financial Statistics (IFS) money market rate. For countries that the data are missing or are not complete, we use data from Datastream, namely for: Chile, Croatia, Cyprus, Greece, Hungary, India, Israel, Italy, Norway, Peru, Saudi Arabia, Slovakia. We use deposit rate (IFS) for China

[3] A few variables are only in annual frequency, if so, we will interpolate the variables to quarterly frequency.

and Turkey, given the lack of data on short-term money market rates in these countries for the whole period studied. For Chile between 1996-1999 we use IDB LMW Interbank Interest Rate.

The data on real effective exchange rates (REER) for each country are taken from the Bank of International Settlements (BIS) http://www.bis.org/statistics/eer/. These are 2010 indices based on CPI. The data are in monthly frequency, thus, they are aggregated to quarterly frequency. The REER time series are in logarithms. An increase in the index indicates an appreciation.

Stock market indices are from Datastream. These are 2010 indices and are in logarithms. In some cases we were not able to find complete series for the whole sample 1995-2016, namely we have missing values for Bulgaria, Croatia, Estonia, Latvia, Lithuania, Romania, Saudi Arabia. We assumed constant indices for the time periods with missing values.

We use the Development Indicator database of the World Bank for construction of the country specific PPP-GDP weights.

We complement the data for domestic economies with commodity price index, namely the level of oil prices. The source of these data is IMF Primary Commodity Prices. We use Crude Oil index, which is the simple average of three spot prices: Dated Brent, West Texas Intermediate, and the Dubai Fateh. The data are in monthly frequency, thus, we aggregate them to quarterly frequency. We transform the time series to 2010 indices and take natural logarithms.

Economic ties between countries are approximated by bilateral flows of exports and imports of goods that are available on an annual basis. The matrixes of trade flows are constructed on the basis of the International Monetary Fund statistics, namely the *Direction of Trade Statistics (DOTS).* These are annual data, so they allow to construct the matrix of trade flows for each year separately and, then, to estimate the model with time-varying link matrixes. Additionally, we use weighting matrixes for broad indices from BIS effective exchange rate statistics. The BIS weights are derived from manufacturing trade flows and capture both direct

bilateral trade and third-market competition by double-weighting (see Klau and Fung 2006 for explanation of the weighting scheme). Importantly for our study, the BIS weights include an adjustment for the fact that substantial portion of China's external trade takes place in the form of re-exports via Hong Kong, and that the official trade statistics of China and its trading partners do not consistently take this into account. This may result in overweight of Hong Kong and underweight of all other trading partners for China.

5. Results

5.1 The baseline model

This section presents the obtained results. We estimated a large number of different model specifications and we chose the model that fits the data best. Our focus was to obtain a stable GVAR model, meaning convergent persistent profiles for the various cointegration relations, eigenvalues lying in the unit circle, and thus non-explosive generalized impulse response functions.

The baseline model includes five variables for each country: real GDP, CPI, stock price index, REER, and short term interest rate, also it includes oil prices as a global variable and real GDP as a foreign variable (see Eq.1). The model uses IMF DOTS matrix of trade flows for 2016. Also we include a dominant unit to model oil prices with one feedback variable (real GDP).

Following, for example, Dees et al. (2007), Cesa-Bianchi et al. (2012) or Bussière et al. (2012) we decided to reduce the number of cointegration relations for the following economies: Argentina (3->1), euro area (5->1), Poland (5->1), Saudi Arabia (1->0), United States (3->1). The decision was based on the shape of persistent profiles. Persistent profiles show the time profiles of the effects of variable or system specific shocks on the cointegration relations in the GVAR model. The value of persistent profiles is unity on impact and, if the vector under investigation is indeed a cointegration vector, it should tend to zero as the time horizon tends to infinity. After the adjustment in the number of cointegration relations we arrived at convergent persistent profiles for all the cointegration relations.

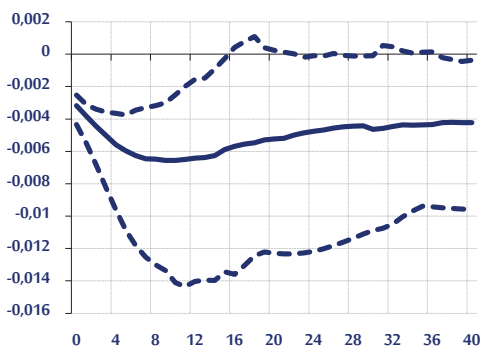
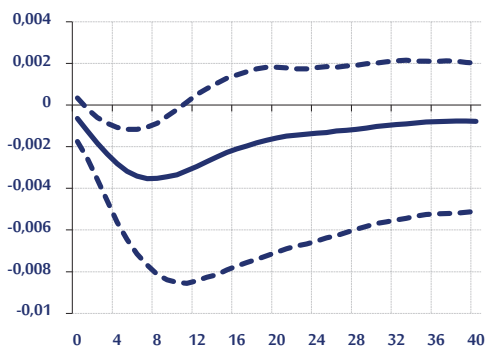
Importantly, we do not impose any restrictions on long-term relations in the GVAR model, as it is often done in the literature (see p.12 Bussière et al. (2012) or Smith and Galesi (2014)). We *let the data speak for themselves*.

In Appendix, Table 2, we present the lag orders and the number of cointegrating relations of the country specific VARX* models in the baseline model.

5.2 Implications of a negative GDP shock in China

A negative one-standard deviation shock to Chinese GDP, which corresponds to an decrease by 0.32% of Chinese GDP at the time of impact, has statistically and economically significant effects on other economies. The peak response of GDP is after 10 quarters and equals to 0.65% (see Figure 1A). As a result the global output decreases by 0.07% on impact, and then decreases by maximum of 0.35% after 7 quarters. The effect becomes insignificant from the 11 quarter onwards (see Figure 1B). In other words, we can easily calculate, that a one percent negative China GDP shock reduces global output by 0.22% in the short run, and then leads to maximum 2% decrease in China GDP and 1% decrease in the global output in the longer term.

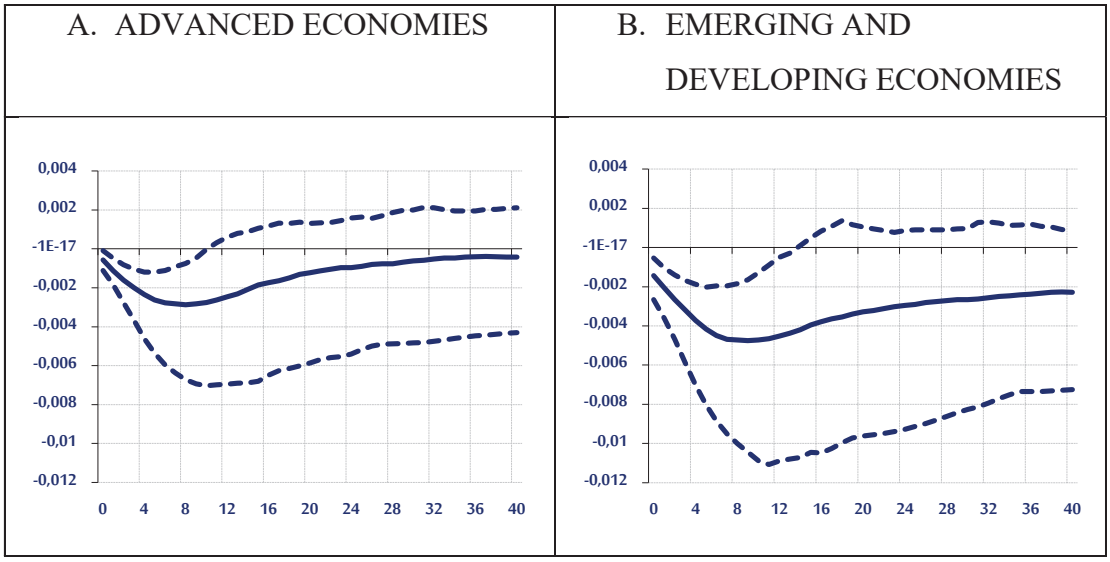
Figure 1. A negative one-standard deviation shock to Chinese real GDP

A. The response of real GDP in China to real GDP shock in China	B. The response of the whole world economy to real GDP shock in China
	

Next we compare the response of advanced economies and emerging and developing economies (E-D economies). We divide the countries into the two groups with accordance to IMF classification. Figure 2 presents impulse response functions of real GDP in advanced and in E-D economies. The reaction in the advanced economies is weaker than in the E-D economies. The maximum reaction of the advanced economies is equal to about 0.29% after 8 quarters, whereas the

maximum reaction of E-D economies is equal to about 0.48% after 9 quarters. The result indicates that emerging market economies, seem to be relatively more vulnerable to spillover effects from the Chinese economy. This is with accordance to the literature, for instance, Gauvin and Rebillard (2015) show that the, so-called, hard landing of China's economy, through its impact on the value of export and the value of investment in mining, will decrease the cumulated economic growth within 5 years by 6% in Latin America, by 4.5% in Asian economies and by less than 2% in advanced economies.

Figure 2. Impulse responses of GDP in advanced and emerging and developing economies to one-standard deviation shock to Chinese GDP



Notes: bootstrap mean estimates with 90 percent bootstrap error bounds

Majority of economies experience a statistically significant drop in GDP after a negative demand shock in China (Figure 3). The maximum strength of reaction varies from -1.10% of GDP (Russia) to -0.07% of GDP (New Zealand), and the timing of maximum reaction is from 4th to 24th quarter. According to the model the most affected economies by the negative China GDP shock are Russia, Singapore, Argentina, Hong-Kong, and Thailand.

Russia and Thailand are large commodity exporters, that depend largely on the export to China. Russia is one of the main China's oil supplier. As it is presented later (see Figure 5) negative demand shock in China causes significant decrease in

oil prices. Similarly Feldkircher and Korhonen (2014) point out that after positive oil prices shock Russia, as one of the biggest oil exporters, experience high increase in GDP, while China experience a large decrease in GDP.

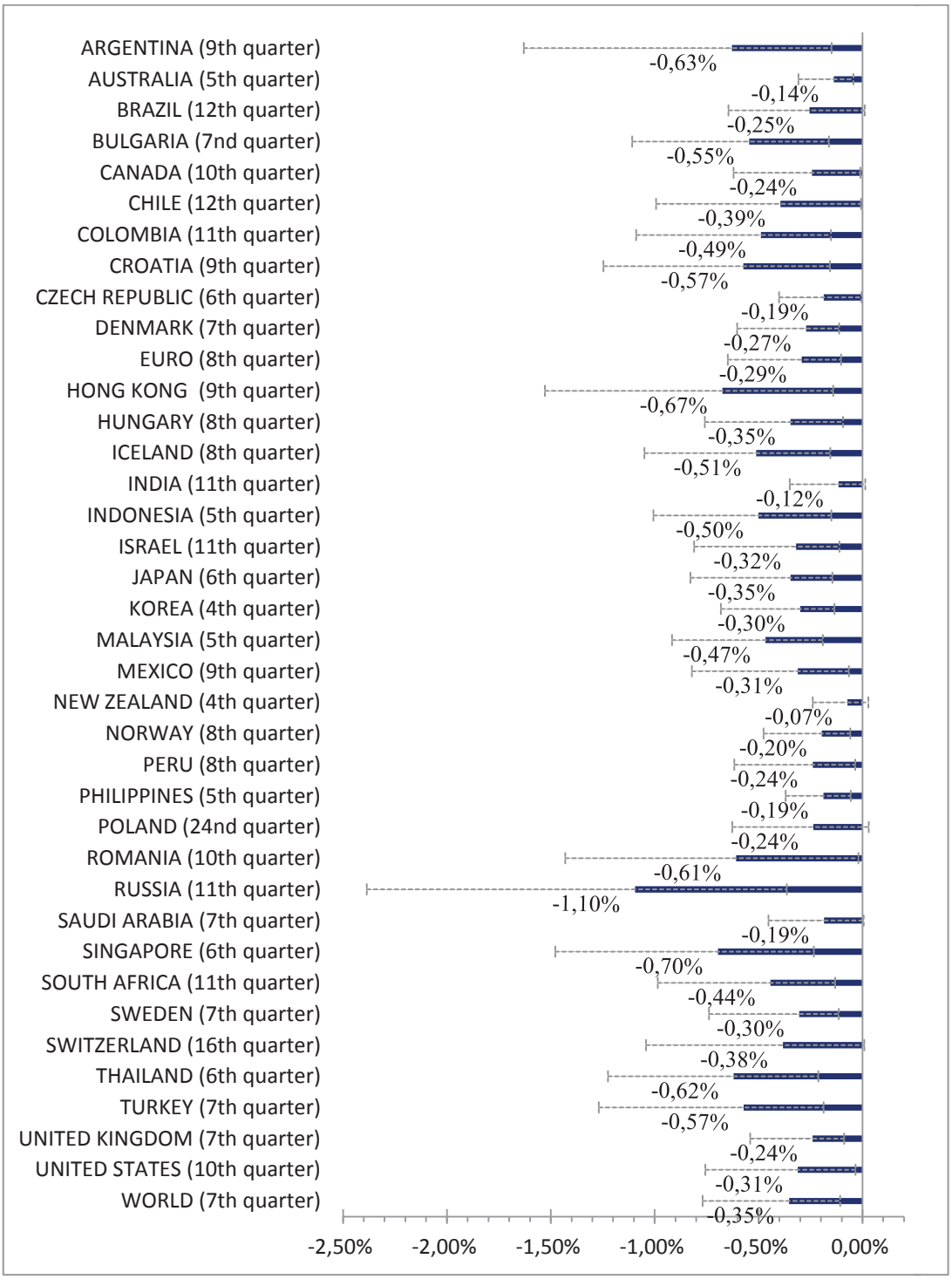
Whereas Singapore and Hong-Kong, as China's close neighbors, may exhibit similar to China business cycles. Also, as we mentioned before, China is a central point of the Asian supply chains.

Large impact of China GDP shock on Argentina is in accordance with the results of Cesa-Bianchi et. al (2012). As they explain it is because of both indirect effects, associated with stronger trade linkages between China and Latin America's largest trade partners, and direct effects stemming from tighter trade linkages between China and Latin America, boosted by the decade-long boom in commodity prices that has inflated trade shares.

On the other hand, countries that seem not to be affected by the negative China GDP shock in our model are Brazil, India, New Zealand, Saudi Arabia, Switzerland, and Poland. The GDP impulse response functions for these countries are not statistically different from zero.

Bussière et al. (2012) as well find that shock to Chinese import has significant effects on Asian countries, among others Singaporean and Thai real output. They argument that the results indicate the presence of strong Asian business cycle and an increased vertical specialisation in international trade among Asian economies. The international fragmentation of production (vertical specialisation) has been increasing over time and, as the authors comment, it is one of the main driving force of the international transmission of business cycle. Also Cashin et al. (2016) report that negative China output shock has large negative impact on less-diversified commodity exporters and Asian countries such as Indonesia, Malaysia, Singapore, and Thailand and lacks significant spillovers to India. This reflects weak trade links between China and India. Inoue et al. (2015), as well, argue that negative China GDP shock mostly influence commodity exporters, such as Indonesia, and countries that largely depend on exports.

Figure 3. The maximum strength and time of GDP reaction in the studied countries after the negative GDP shock in China

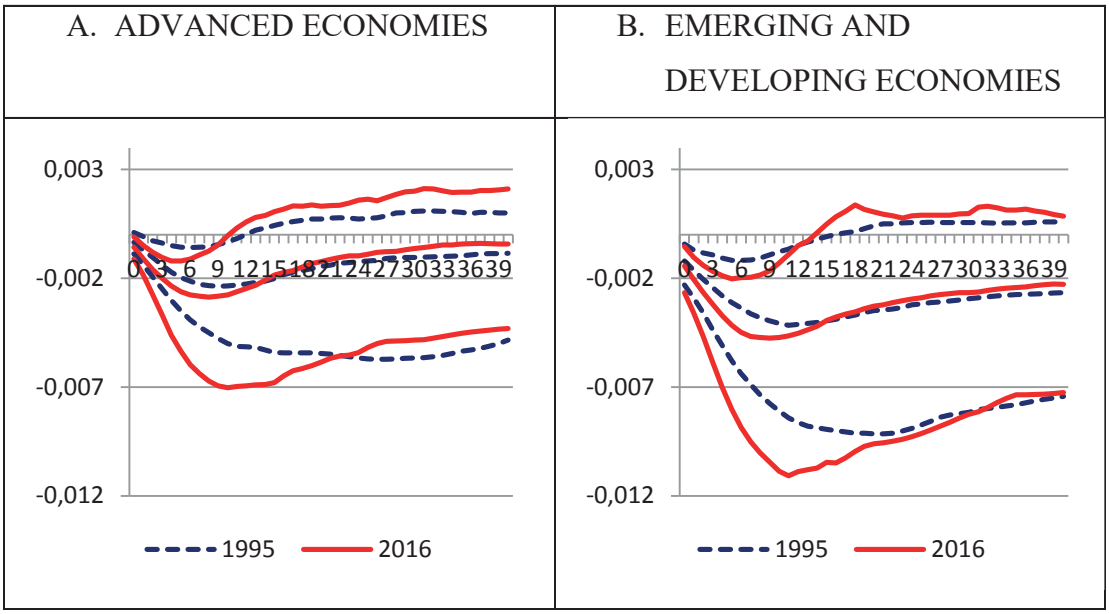


Notes: the quarter of maximum reaction in parenthesis; black dotted lines show 90 percent bootstrap confidence bounds

We compare the reactions of GDP in the chosen economies when estimating the model with 1995 and 2016 trade flow matrixes. By doing so we quantify how changed trade patterns have altered the transmission of shocks from Chinese economy.

Figure 4 compares the impulse responses of GDP to negative GDP shock in China when using 1995 and 2016 trade weights. It turns out that the reaction is slightly stronger and faster both in the advanced and in the E-D economies when we use more recent trade weights. The maximum reaction of GDP in the advanced economies appears after 8 quarters and is equal to 0.29% when using 2016 trade matrix, and it appears after 10 quarters and is equal to 0.24% when using 1995 trade matrix. Similarly, for E-D economies, the maximum reaction appears after 9 quarters and is equal to 0.48% when using 2016 trade matrix, and it appears after 11 quarters and is equal to 0.42% when using 1995 trade matrix. This shows that the application of fixed trade matrix for 1995 and the application of fixed trade matrix for 2016 give quite similar results. It means that changes in the structure of trade in time do not affect the results significantly. This is an argument for using the fixed and not necessary the floating trade matrix (see Section 5.4 – Robustness of the results).

Figure 4. Impulse responses of GDP in advanced and emerging and developing economies to one-standard deviation shock to Chinese GDP with 1995 and 2016 trade flow matrixes



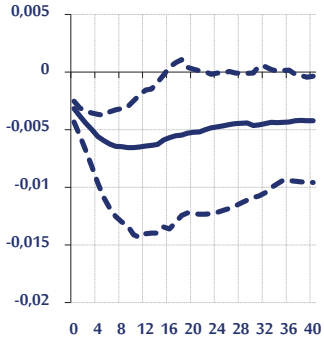
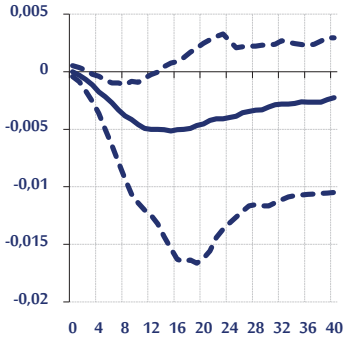
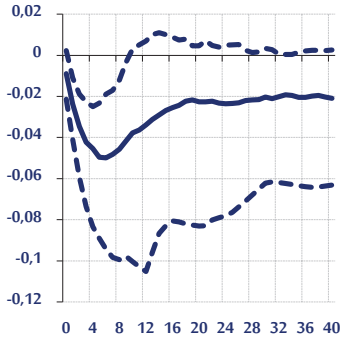
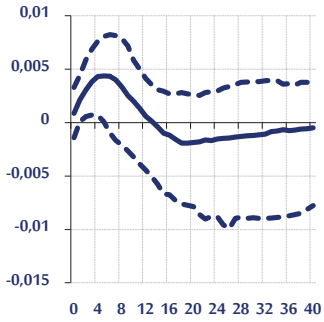
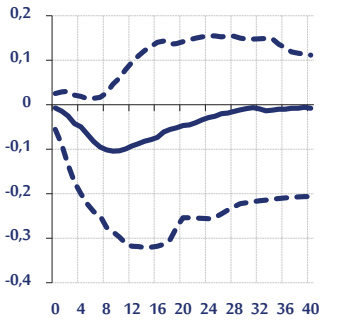
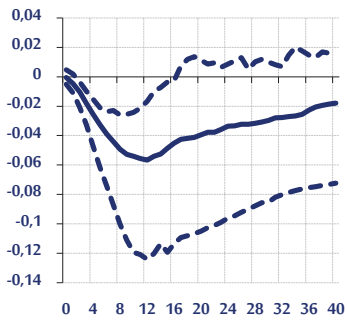
Notes: bootstrap mean estimates with 90 percent bootstrap error bounds; red line – 1995; blue dotted line – 2016.

Figure 5 shows the response of the Chinese economy to one-standard deviation negative shock to GDP in China. As the result of negative demand shock CPI decrease, the maximum reaction of prices is -0,5% after 15th quarter. CPI decrease steadily from the first quarter onward, but the reaction becomes statistically insignificant from 14th quarter. Stock prices decrease as well, the maximum reaction being -5% in the 6th quarter. The reaction is statistically significant until the 9th quarter. REER appreciates in the short run, and then depreciates, but the reaction is not statistically significant from the 6th quarter onward.

The reaction of exchange rate seems to be counterintuitive, as one would rather expect the exchange rate to depreciate after the negative demand shock. China, however, has a strictly controlled currency policy, it regulates trading activity and tries to control daily movements of the yuan on the forex market. China's government has fixed it currency to US dollar (8 yuan to the US dollar) in 1995 and has gradually widen the trading band since 2005. Also the yaun is not fully convertible, meaning that investors who want to buy yaun must do it directly in the China's cental bank. Thus, often interventions of the government in the forex market affect the value of yuan, that is not fully determined by the market forces.

Next, after the negative GDP shock interest rate decreases, and the maximum reaction is -10% after 10th quarter, but this reaction is not statistically significant. Also oil prices decrease by maximum of 5.7% after 12th quarters. The same result was found, for example, by Cashin et al. (2016), who argue that China's rebalancing (slowdown of the economy) affects the economies of commodity exporters mainly by its impact on global demand for commodities and associated prices, that translates to lower overall economic growth in these countries.

Figure 5. Transmission of the negative GDP shock in Chinese economy

Response of GDP to Chinese GDP shock	Response of CPI to Chinese GDP shock	Response of stock prices to Chinese GDP shock
		
Response of REER to Chinese GDP shock	Response of short term interest rate to Chinese GDP shock	Response of oil prices rate to Chinese GDP shock
		

5.3 Implications of a negative equity prices shock in China

Between June 2015 and February 2016 increased volatility in the Chinese stock exchange was observed. The benchmark Shanghai Composite crashed, wiping out over 40% of its value (see Figure 6). Authorities introduced a number of measures to stop the losses, such as banning large shareholders from selling, outlawing forms of short-selling, chasing down individuals they blamed for manipulating the markets, and a circuit breaker mechanism[4]. As the result of the crash on China stock exchange, large decreases were observed in the international stock markets. This section examines the international spillover effects of the surge in China's stock exchange volatility.

Figure 6. Shanghai Composite Index

We concentrate on the result of decrease in stock prices in China. The negative Chinese stock price shock is presented in Figure 8. The shock is equal to one standard deviation of Chinese stock prices, that is 5% decrease in stock prices on impact. The shock is temporary and becomes statistically insignificant in three quarters.

Figure 7 presents the response of stock indices in the advanced and the emerging and developing economies to negative stock price shock in China. The impulse response function for advanced economies is not statistically significant, that seems to suggest that the decrease in stock prices in China does not have a

[4] The breaker mechanism, however, created panic selling and had to be withdrawn.

significant effect on stock markets in these countries. This result is intuitive, because China has weaker financial than trade linkages with advanced economies, China's capital account is among the most closed in the world, and the access of foreigners to Chinese stock markets and Chinese to foreign stock markets is limited.

Whereas, the reaction for emerging and developing countries is statistically significant for the first two quarters. The maximum reaction of stock prices in E-D economies is 3% on impact and becomes statistically insignificant after two quarters. The intuition behind the result is that China is financially and economically more strongly connected with emerging markets than with advanced economies (yuan payments, Chinese banks loans for infrastructure development) and China is often included in the same basket as other emerging economies (falls in the Chinese stock exchange may automatically lead to falls in other emerging markets stock exchanges, such as Brazil, Russia, or Turkey).

Figure 7. Response of stock indices in the advanced and the emerging and developing economies to negative stock price shock in China

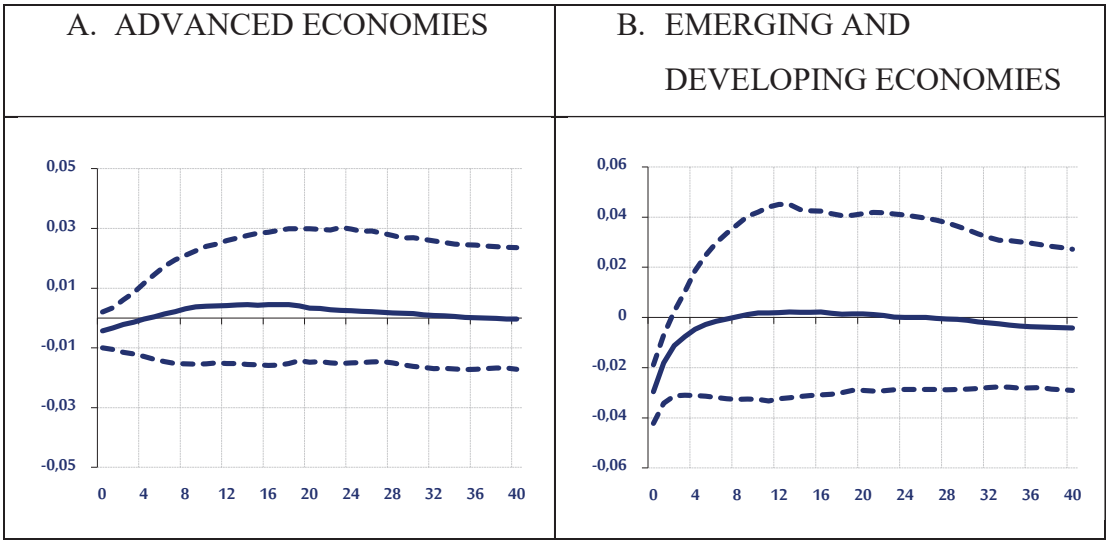
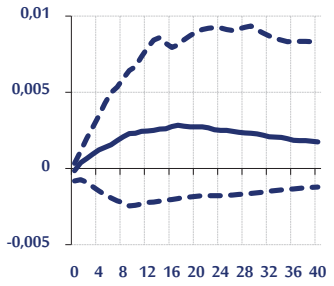
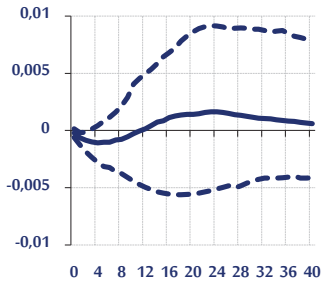
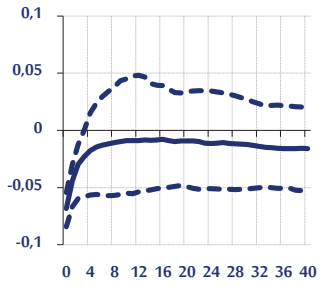
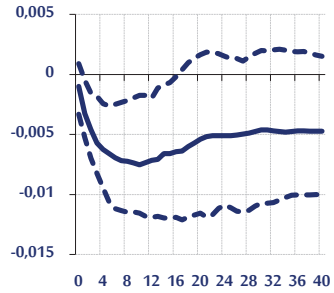
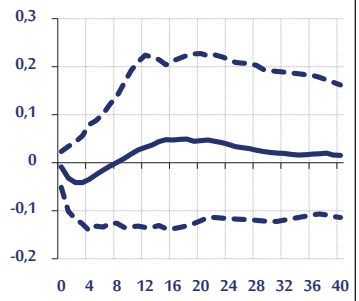
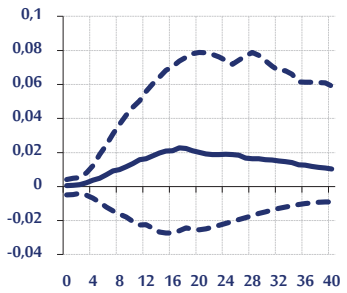


Figure 8 shows the response of the Chinese economy to one-standard deviation shock to stock prices in China. The responses of real GDP and short-term interest rate in China are not statistically significant. The fact that real GDP in China does not react to changes in stock price index, means that Shanghai Composite index

is not a leading economic indicator for real economy in China. This may be also confirmed by weak correlation of GDP and Shanghai index in China.

One may observe a decrease in CPI in the first and second quarter after the impact and large depreciation of yuan (maximum response being 0.75% in 10th quarter), which is statistically significant until 16th quarter. This reflects the fact, that People's Bank of China devaluated the yaun around the time of the largest turbulence on the stock exchange.

Figure 8. Response of the Chinese economy to negative one-standard deviation shock to stock prices in China

Response of GDP to stock price shock	Response of CPI to stock price shock	Response of stock prices to stock price shock
		
Response of REER to stock price shock	**Response of short term interest rate to stock price shock**	**Response of oil prices to stock price shock**
		

5.4 Robustness of the results

We run many series of robustness checks. Below we report only the most interesting findings.

We test the robustness of the results to different trade matrixes. As a trade matrix we use weighting matrix for broad indices from BIS effective exchange rate statistics as well as we use floating trade matrix based on DOTS statistics instead of the fixed one. In both cases we confirm the result that emerging and developing economies react stronger to China's GDP and stock prices shocks than the advanced economies.

However, for BIS trade matrix we need to reduce the number of cointegrating relations for more than a half of analysed economies to arrive with the stable model. The results of estimating this model show the permanent China's GDP shock meaning the decrease in GDP of about 1%, leads to the similar decrease in the global GDP. Whereas, for the floating trade matrix many GDP impulse response functions for particular economies get statistically insignificant.

Moreover, we find that some impulse response functions largely depend on the number of cointegration relations used. It is the case of Saudi Arabia. When we apply a model with 1 cointegration relation for this country, we end up with much stronger reaction of GDP to China GDP shock. The reaction of GDP for Saudi Arabia in such model is very similar to the reaction of GDP for Russia in the presented baseline model. It is not surprising, as Saudi Arabia and Russia are two main China's oil source of imports. Also, the change in the number of cointegration relations makes the reaction of GDP in Croatia, Romania, and Turkey even stronger than in our baseline model.

6. Conclusions

The article pays attention to the spillover effects that originate in the Chinese economy. China has emerged as a global economic power, that recently has experienced a slowdown of economic growth and also turbulences in the domestic equity markets. We investigate empirically how negative shocks to China GDP and to China stock prices transmit internationally.

In order to do so we create and estimate the GVAR model that allows to model the economic linkages between a large number of economies. We obtain the results that are intuitive and are in accordance with the presented literature.

We find that a one percent negative China GDP shock reduces global output by 0.22% in the short run, and then leads to maximum 2% decrease in China GDP and 1% decrease in the global output in the longer term. The reaction being weaker in the advanced economies than in the emerging and developing economies.

Also we end up with slightly weaker GDP impulse responses when estimating the model with 1995 trade flow matrix in comparison with the model with 2016 trade flow matrix. This shows that changes in the structure of trade in time do not affect the results of our model significantly.

According to the model the most affected economies by the negative China GDP shock are Russia, Singapore, Argentina, Hong-Kong, and Thailand. Russia and Thailand are large commodity exporters, that depend largely on the export to China. Whereas Singapore and Hong-Kong, as China's close neighbors, may exhibit similar business cycles. Also, as we mentioned before, China is a central point of the Asian supply chains.

Our results show that the negative stock prices shock in China is associated with a decrease in stock indices in the emerging and developing economies as well as large depreciation of yuan. The results, however, do not show a statistically significant decrease in stock price indices in the advanced economies. Such results are not surprising, mainly because of financial linkages of China with the analysed

economies and because of the Chinese central bank policy, that used to decrease the value of yuan after the major negative equity price shocks.

Also the response of real GDP in China to stock prices shock is not statistically significant. This shows that Shanghai Composite index is not a leading economic indicator for real economy in China.

Appendix

Table 2. Lag orders and number of cointegrating relations for country specific VARX*(p,q) models in the baseline model

country	VARX* order		No. of cointegrating relations	country	VARX* order		No. of cointegrating relations
	p	q			p	q	
Argentina	2	1	1	Korea	1	1	4
Australia	2	1	2	Malaysia	1	1	2
Brazil	1	1	1	Mexico	1	2	4
Bulgaria	2	1	3	New Zealand	1	1	2
Canada	1	1	2	Norway	1	1	2
Chile	1	1	3	Peru	1	1	2
China	1	1	3	Philippines	1	1	3
Colombia	1	1	2	Poland	1	1	1
Croatia	1	1	1	Romania	1	1	3
Czech Republic	1	1	2	Russia	2	1	4
Denmark	1	1	3	Saudi Arabia	1	1	0
Euro	1	2	1	Singapore	1	1	1
Hong Kong	1	1	2	South Africa	1	1	3
Hungary	1	1	2	Sweden	1	1	2
Iceland	1	1	3	Switzerland	1	1	3
India	1	1	3	Thailand	1	1	3
Indonesia	1	1	2	Turkey	1	1	2
Israel	1	1	2	United Kingdom	1	1	2
Japan	1	1	2	United States	1	1	1

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