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Impact of China on World Commodity Prices and Commodity Exporters

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Abstract

We study the effect of a domestic shock in China on the real economy and financial markets of a commodity exporting country. We estimate a dynamic factor model using Bayesian methods to identify a China factor and a global factor using monthly macroeconomic data from China and rest of the world. We, then, assess implications of the China factor on global commodity prices and macroeconomy of a commodity exporting nation in a reduced form Bayesian VAR. A negative China shock causes fall in global commodity prices leading to output loss and stock market fall in these countries. China shock affects output of only a subset of countries in our sample compared to US shock, which affects all countries. Stock markets of commodity dependent countries respond strongly and more quickly to China shock than to US shock. China shock also has more persistent effect on commodity prices than US shock.

Keywords: China; Commodities; Bayesian VAR; Dynamic Factor Model; Emerging Market Economies

I. Introduction

Last decade saw a boom in the world commodity prices, both oil and non-oil. The boom brought windfall gains to the commodity exporting countries and also accelerated their economic growth through improved terms of trade, higher demand for their exports and therefore, also through higher productive investment. This commodity price super-cycle has largely been attributed to the industrialization and urbanization of China (Erten and Ocampo, 2013). China grew rapidly during 1980 to 2011. Gauvin and Rebillard (2015) find that between 2003 and 2011 most of the increase in the global demand for copper and iron ore came from China; the demand from other regions was more or less stable. During this period, China's demand for iron ore increased by 213 percent and copper by 157 percent. Oil demand, on the other hand, increased modestly, by 68 percent.

The miraculous growth of the Chinese economy finally started slowing in 2011. Growth has been decelerating since. Most studies forecasting China's growth do not find any possibility of return to the previous path and the estimates remain 5 percent a year or below at least for the next five years (Albert et al., 2015; Haltmaier, 2013; Hoffman and Polk, 2014; Nabar and N'Diaye, 2013; Pettis, 2013). From year 2009 onwards, there was a surge in infrastructure investment by the Chinese government, in order to offset the decline in growth caused by falling exports, which had resulted from the global financial crisis. This pumped up the demand and price of commodities, especially industrial metals, in the global market. As the Chinese government started on the path of restoration of the internal balance of the economy by encouraging the share of consumption in GDP and reducing overinvestment (Lee et al., 2012), world commodity demand and prices took a hit.

While it is famously said "when US sneezes, world gets a cold", China's reputation as a voracious commodity consumer certainly makes us say "when China sneezes, global trade flows catch a cold". Many commodity exporting countries have been struggling with low growth rates since the global commodity price slump began (IMF, 2015). However, the impact of this price collapse is different across exporters. Brazil and Russia have been in recession since the second and third quarter of year 2014, respectively, while Canada faced only a short recessionary stint in the first half of 2015.

These developments have spurred a lot of research devoted to analyzing China's impact on the global economy. Previous studies looked at the impact of China, and emerging Asia in general, on global commodity prices. Hicks and Killian (2013) found that unexpected economic growth in emerging Asia was primarily responsible for the rise in global oil price between mid-2003 to mid-2008. Francis (2007) documented the impact of China on oil and metals prices. Arbatli and Vasishtha (2012) found that emerging Asia had a large role to play in the global metals' price increase but limited role in oil price increase. Farooki (2010) attributed the rise in base metals price to increasing demand created by urbanization and industrialization in China, which the exporting (supplier) countries found hard to keep pace with, due to capacity expansion constraints. Erten and Ocampo (2013) made a similar observation and also showed that non-oil commodity price booms are mainly demand-driven.

There is also a growing research on the impact of a shock originating in China on other countries. Feldkircher and Korhonen (2012) find that a one percent positive shock to Chinese output leads to a 0.1 to 0.5 percent rise in output for most large countries. Accounting for trade linkages, financial variables and oil prices, Cashin et al. (2012) find that countries in Middle Eastern and North African region are more sensitive to developments in China than to shocks in the Euro area or the United States. Rebucci et al. (2012) show that the long-term impact of a China GDP shock on the typical Latin American economy has increased by three times since mid-1990s. In terms of the main goal, our paper is closely related to Gauvin and Rebillard (2015), henceforth GR. Like us, they also assess the impact on China on other countries, with a focus on trade and commodity price channels. Their study includes all the countries present in our sample, which enables comparison between our study and theirs.

All these previous works, studying China's effect on other countries, use a global vector autoregression (GVAR) framework. The GVAR model comprises a compact model of the world economy designed to explicitly model the economic and financial interdependencies at national and international levels. The design of this framework, along with the easy availability of the GVAR Toolbox, has increasingly made it the workhorse for assessing international transmission of shocks among policy institutions.

Although, with the rise of China, examining China's impact on global economy has become an interesting exercise, there are certain limitations to its usefulness. Fernald, Spiegel and Swanson (2014) express skepticism about the quality of Chinese data. In their paper, they estimate the effects of Chinese monetary policy on the Chinese economy. In order to overcome the data quality issue, they employ a factor-augmented vector autoregression (FAVAR) developed by Bernanke et al. (2005). That is, they take a broad and expansive approach and use a large number of series associated with Chinese economic activity and inflation to estimate the true underlying, latent values of these series.

In our study, we examine a sample of commodity exporting countries and investigate whether and how a Chinese domestic shock affects their macroeconomies, focusing on the commodity market. Giving due importance to the Chinese data quality issue, we follow Fernald, Spiegel and Swanson (2014) and deploy the FAVAR methodology. Our sample includes ten advanced and emerging countries, both oil exporters and metal exporters. We use monthly data over period 2000:M1 to 2015:M9. We examine two channels of shock transmission in this system: commodity price and real exports to China. If a positive shock to the Chinese economy raises its demand for commodities, it increases global commodity prices. This is a positive terms of trade (ToT) shock for a commodity exporter. The increase in demand also causes increase in its exports to China, which is the second channel of transmission. Our model also looks at the role played by exchange rate in shock transmission.

We find that a negative shock to Chinese economic activity decreases the output of many commodity exporting countries. We also find a fall in the stock market of most of these countries and that their currencies depreciate. In the global commodity market, the shock causes a fall in commodity prices. We also compute the effect of US economic activity shock for comparison purpose. While US shock affects all countries in our sample, China shock affects only a subset of countries. For some countries, like Brazil and Russia, China shock has bigger effect on output than US shock. We find evidence of stronger and quicker response of stock markets of more commodity-dependent countries to China shock relative to US shock. Oil price is more sensitive to both China and US shocks, as compared to metal prices. Compared to US shock, China shock has more persistent effect on commodity prices.

For both oil and metal exporters, commodity price emerges as an important channel of China shock transmission whereas the quantity of exports to China plays a limited role. We also find evidence of a larger effect of China on emerging countries as compared to advanced countries.

The contribution of this paper is twofold. First, given the issue of the quality of Chinese data, we employ a factor-augmented VAR framework to study the effect of China shock. This method reduces the dependence of estimation on a single measure of output and therefore the results are more reliable. While deriving the China economic activity factor we allow for a global factor. Exports to advanced countries constitute a large part of China's income and therefore, China's output is affected by these countries. Allowing for global factor helps in focusing on shocks which originate in China's domestic economy. Second, our study provides crucial findings on the effect of China on output and stock market of commodity exporting nations. In doing this, we compare the results with those of a US shock in the same empirical framework which helps us benchmark the relative importance of China in world economy.

The rest of the paper is organized as follows. Section II presents the econometric methodology and estimation strategy. Details of data are provided in Section III. Section IV presents the results. Section V discusses the robustness exercises and section VI concludes.

II. Econometric Methodology and Estimation Strategy

There is a lot of skepticism around the quality of Chinese data. In order to avoid dependence on a single series, we follow Fernald, Spiegel and Swanson (2014) and Bernanke et al. (2005) and deploy a dynamic factor model to estimate an underlying Chinese economic activity factor using many observable macroeconomic series. Then we use this latent factor as an exogenous variable in a reduced form VAR of a commodity-exporting country. Such a VAR, where a latent factor is included as one of the variables, is commonly known as a factor-augmented VAR (FAVAR).

Now we describe the models in detail. We describe the model and estimation strategy for dynamic factor model first, and then for FAVAR model. Our data is at monthly frequency.

II.1.1 Dynamic Factor Model

The idea behind factor models is to decompose the driving forces of a possibly large number of series into a small set of orthogonal latent variables common to all series and a group of idiosyncratic disturbances. The latent variables are called ‘factors’ and they are responsible for all comovements in the data. Idiosyncratic disturbances, on the other hand, are specific to the series and orthogonal to the factors. Geweke (1977) was the first to propose a dynamic factor model as a time-series extension of the factor model previously developed for cross-sectional data. Sargent and Sims (1977) showed that two dynamic factors could explain a large fraction of the variance of important U.S. quarterly macroeconomic variables, including output, employment, and prices. Later, many studies; for example Giannone, et al. (2004) and Watson (2004), confirmed this central finding that a few factors can explain a large fraction of the variance of many macroeconomic series.

In our study, we use a dynamic factor model specification as in Chatterjee (2016):

$$X_t = B_0 F_t + B_1 F_{t-1} + \varepsilon_t \tag{1}$$

where X_t represents a high-dimensional vector of time-series variables, F_t represents a vector of latent factors, much smaller than X_t ; and ε_t is a vector of idiosyncratic errors.

Given the central role of the latent China factor in our exercise, it becomes pertinent to identify it correctly. As exports constitute a huge share of Chinese GDP, there lies a danger of wrongly identifying a global shock as a China shock since exports affect economic activity in China. We account for these shocks by including several US macroeconomic series in our dynamic factor model and allowing for a US (global) factor.

Accordingly, in the above model the $[N + M] \times 1$ vector X_t contains macroeconomic series observable at time t such that N is the number of US variables and M is the number of China variables. F_t is a vector of two latent factors –US factor and China factor, the $[N + M] \times 2$ matrix B_k is the factor loading of X_t for F_{t-k} , k = 0,1 and ε_t is a $[N + M] \times 1$ vector of idiosyncratic errors. The factor loadings indicate the importance of the factors in explaining the variance of an observable series.

Each of the idiosyncratic error series, $\varepsilon_{i,t}$, *i=1 to N+M*, is assumed to be normally distributed. They may be serially correlated and follow a first-order autoregression:

$$\varepsilon_{i,t} = \varphi_1^i \varepsilon_{i,t-1} + \eta_{i,t} \tag{2}$$

where φ_1^i is the autocorrelation coefficient.

The factors and the innovations, $\eta_{i,t}$, are assumed to be zero mean, contemporaneously uncorrelated normal random variables,

$$\eta_{i,t} \sim N(0, \sigma_i^2) \tag{3}$$

$$F_t \sim N(0, \Sigma)$$

Therefore Σ is a diagonal matrix, with the variance of the factors, $\sigma^2_{F_t{}^{China}}$ and $\sigma^2_{F_t{}^{US}}$, as its diagonal entries. The idiosyncratic errors are orthogonal to the factors. The time paths of the factors $\{F_t\}$, the factor loadings B_k**,** the autocorrelation coefficients φ_1^i, the error variances σ_i^2 and the factor variances $\sigma^2_{F_t{}^{China}}$ and $\sigma^2_{F_t{}^{US}}$ are jointly estimated.

II.1.2 Estimation Strategy for Dynamic factor Model

We define the US factor as factor 1, and the China factor as factor 2. Then, in equation (1), B_k (1) refers to the factor loading on US factor and B_k (2) refers to the factor loading on China factor, for the observed variables at lag k. The estimation of dynamic factor model requires some identification and normalization restrictions. Identification restrictions are imposed in order to facilitate the interpretation of factors as representing shocks of different nature. Here, we make the assumption that China factor does not affect the US variables. In other words, the China factor loading for US variables is zero. Hence, in equation (1)

$$B_k^{X_{i,US}}(2) = 0$$

for all observed US series, $X_{i,US}'s$, and at all lags, *k*. This assumption attributes any comovement of the US and China variables to the US factor. An advantage of this assumption is that it results in China factor representing the domestic economy solely. This facilitates examining the effect of shocks which originate in China's domestic economy. Nevertheless, in the Robustness section, we also show that results are largely unchanged when we relax this assumption and allow China factor to affect the US variables with a lag.

Along with identification restriction, we also need to impose normalization restriction, in order to overcome the well-known problem of unidentified models resulting from rotational indeterminacies of factors and loadings. Following Justiniano (2004), Kose et al. (2007), we normalize the contemporaneous factor loading of the 'US Industrial Production' for the US factor, and the contemporaneous factor loading of 'China Industrial Production' for the Chinese factor, to unity:

$$B_0^{IP_{US}}(1) = 1, \qquad B_0^{IP_{China}}(2) = 1$$

This assumption helps us to identify the scale and signs of the factors separately.

Two approaches have become popular for the estimation and identification of factor models: the analysis of principal components and the use of Markov Chain Monte Carlo (MCMC) methods. Due to its simplicity and the availability of high speed computers, principal component analysis is extensively used for both static and dynamic factor models, extending to models using hundreds of series.

As Justiniano (2004) and Kose et al. (2008) explain, principal component method is, however, not well suited for estimating models under exclusion restrictions. Model estimation using principal component requires deriving factors from the variance or spectrum of all series simultaneously, and therefore, it becomes inappropriate when a subset of variables is assumed to relate to the factors in a different manner than the rest of the variables. In other words, factors cannot be derived in one step. Some studies, for example Lippi and Reichlin (2001), implement an ad hoc multi-step approach in which at every step some factors are derived. Adding more steps, however, also increases estimation errors in subsequent steps.

Therefore, we follow Justiniano (2004) and Kose et al. (2008) and use the MCMC method which easily accommodates restrictions on how the factors affect subsets of series. The following paragraph outlines our estimation technique.

We need to use special techniques to estimate the model as the factors are unobservable. Following Chatterjee (2014), we apply the Bayesian posterior simulation method to estimate the dynamic latent factor model. The estimation procedure is based on the following vital observation: if the factors were observable, under a conjugate prior, the models (1) - (3) would be a simple set of regressions with Gaussian autoregressive errors; that simple structure can, in turn, be used to determine the conditional normal distribution of the factors given the data and the parameters of the model. This conditional distribution can, then, easily be used to generate random samples, which can serve as proxy series for the unobserved factors. As the full set of conditional distribution is known – parameters given data and factors, factors given data and parameters – it is possible to generate samples from the joint posterior distribution for the unknown parameters and the unobserved factors using MCMC procedure. The process is iterated a large number of times. This sequential sampling of the full set of conditional distributions is known as Gibbs sampling. Under the regularity conditions satisfied here, the Markov chain so produced converges, and yields a sample from the joint posterior distribution of the parameters and the unobserved factors, conditioned on the data.

We implement the model allowing for one lag in both, the factor loading[1] and the serial correlation of idiosyncratic errors. Following Chatterjee (2016), we specify the prior on all factor loading coefficients and the autoregressive parameters as N (0, 1). The prior on the error variances and the factor variances is Inverted Gamma (6, 0.001), which is very diffuse, allowing for considerable parameter uncertainty.

II.2.1 Factor-Augmented VAR Model

After we estimate the US factor and China factor using the above model, we estimate a reduced form FAVAR for each commodity exporting country using these factors as exogenous variables. The assumption is valid because we consider small open economies which we do not expect to affect either China or the US economy. To be precise, we use the following model:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \sum_{i=0}^{q} D_i F_{t-i} + CZ_t + \nu_t$$

[1] In the robustness check section we show results while allowing more lags of the factors and idiosyncratic errors in the dynamic factor model.

where Y_t is a $R \times 1$ vector of endogenous variables of a commodity exporting country, F_t is a 2×1 vector of China factor and US factor, Z_t is a $S \times 1$ vector of other exogenous variables including a constant term and a few dummy variables representing global events, A_i's are $R \times R$ coefficient matrices, D_i's are $R \times 2$ coefficient matrices, C is a $R \times S$ coefficient matrix and ν_t is a $R \times 1$ vector of errors. It is assumed that for ν_t,

$$\nu_t | Y_{t-1}, \dots, Y_{t-p}, F_{t-1}, \dots, F_{t-q}, Z_t \sim \mathbb{N}(0_{R\times 1}, \omega)$$

where $0_{R\times 1}$ is a $R \times 1$ vector of zeros and ω is a $R \times R$ positive definite matrix.

The baseline specification includes the following endogenous variables of a commodity exporting country: industrial production index as a measure of output, consumer price index as the price level, three-month interest rate as a monetary policy measure, USD exchange rate and a stock market index. Output and price level are included in the FAVAR as we are assessing the effect on the macroeconomy of a country. Central banks often respond to external shocks in order to stabilize the economy. Therefore, short-term interest rate is included to capture this response. In an open economy, flexible exchange rate absorbs the effect of an external shock and help in output stabilization. This justifies their inclusion in the model. We include the stock market index in order to include a forward looking variable in our model[2] and also to assess the effect of shock on financial markets.

Along with these, the model includes the two latent factors- China factor and US factor, as exogenous variables. Lastly, we include dummy variables which indicate Euro debt crises. Along with these, we include country specific dummies for some countries to account for crisis episodes. We use a recursive ordering of the endogenous variables in the order listed above[3], which is standard in the literature, to derive the structural VAR coefficients, which are required to graph the impulse response function of the variables to a shock in the latent factor.

[2] It has become a common practice to include a forward looking variable in a monetary VAR in order to remove the price puzzle.

[3] In the robustness check section we show that the results are not sensitive to an alternate ordering of the variables.

In order to explore trade as a potential transmission channel through which a Chinese shock could affect an economy, we add the variables – 'global commodity price' and 'real exports to China' - to the FAVAR. We call this model 'expanded FAVAR'. The endogenous variables are ordered as follows: commodity price, output, price level, interest rate, export to China, USD exchange rate and stock market index[4]. Commodity price is ordered before the industrial production index under the assumption that a small open economy takes international price as given[5]. Also, putting commodity price before exchange rate is consistent with the finding in Chen et al. (2010) that commodity prices help forecast exchange rate of commodity exporters.

II.2.2 Estimation Strategy for FAVAR

The FAVAR is also estimated using the Bayesian approach with Minnesota-type priors that are laid out in Sims and Zha (1998). We use the first six months of data as initial conditions. The Minnesota-type prior combines a prior belief that the dynamics of each variable in the FAVAR is well represented by a random-walk model and a belief that favors unit roots and cointegration of variables. This type of prior has become popular in standard VAR models which include variables exhibiting persistent dynamics. The prior's ability to reduce the problem of dimensionality helps in better forecast performance (Canova, 2007). We follow Sims and Zha (1998) when choosing the hyperparameters of the prior distribution. The Gibbs sampler is used to make draws from the posterior distribution of the FAVAR for the commodity exporting countries.

III. Data

Given the availability and quality of Chinese data and the fact that China has undergone rapid institutional and structural changes since 2000 (Fernald, Spiegel and Swanson, 2014), we begin our sample from this year. We estimate the models using monthly data for the period January 2000 to September 2015. All not seasonally adjusted series, other than interest rate, exchange rate and stock market index, are deseasonalized using Census X-12 ARIMA package.

[4] In the robustness checks we show that alternate ordering of variables does not change our main results.

[5] In the robustness check section we show that the results are unchanged when we order commodity price after the macroeconomic variables.

In the dynamic factor model, for the US, the following five series are used: i) industrial production index, ii) real personal consumption expenditure, iii) total non-farm employment, iv) heavy weight truck retail sales and v) University of Michigan: consumer sentiment index. We also use additional variables during our robustness checks. The data is obtained from the Federal Reserve database. For China, we use nine variables: 1) industrial production index, 2) electricity production, 3) real retail sales, 4) consumer expectation index, 5) rail freight traffic, 6) real estate investment: residential building, 7) total loans, 8) fixed asset investment and 9) floor space started: commodity building[6]. The data for China are from CEIC Asia Database. Only the industrial production index series is taken from Datastream. We have attempted to select similar variables for China and US. In the Robustness section, we show that taking different combinations of China and US variables does not affect our main results.

There is a typical challenge in handling Chinese data. The Chinese New Year has a large influence on the domestic economic activity. However, it can fall anytime in January and/or February. Simple seasonal adjustment cannot fully account for this. We, therefore, follow Fernald, Spiegel and Swanson (2014)[7] and make an adjustment for the event, same as theirs, before doing the normal seasonal adjustment. So, for each observable Chinese series, we first average the values of the series for January and February. Then we distribute the average value across the two months by assuming that the growth from January to February equals the growth from December to January. Although, this implies some loss of information for the two months, we avoid the large swings in data.

Finally, we take the seasonally adjusted month-to-month growth rates (calculated as 100 times the log-change) of all series for the US and China. This becomes the input data for the dynamic factor model.

We examine the following 10 commodity exporters: Australia, Brazil, Canada, Chile, Colombia, Malaysia, Mexico, Peru, Russia and South Africa. Among these Australia, Brazil, Chile, Peru and South Africa are primarily metal exporters. Chile and Peru mainly export copper. Rest all are oil exporters. Accordingly, in the FAVAR model, for the global commodity prices we use- S&P GSIN, (USD) price index for heavy metals, for

[6] We have taken the macroeconomic series for which there were minimal missing observations for our sample period.

[7] They provide the codes on their websites.

Australia, Brazil and South Africa and; Brent oil price for Canada, Colombia, Malaysia, Mexico and Russia. For Chile and Peru we use copper price. S&P GSIN data is collected from Bloomberg. Other commodity prices are taken from IMF database.

The bilateral trade data with China is obtained from IMF Direction of Trade Statistics (DOTS) database. We use the total exports to China for each country, as reported by the individual countries. The data is in current US dollars. We convert it into year 2000 constant US dollars using monthly US consumer price index for urban consumers. The data is taken from Federal Reserve. Although 'commodity exports to China' would be a more appropriate series for our purpose, unavailability of monthly bilateral commodity trade data for most of the sample period limits us from using that. Using the annual bilateral commodity export data from United Nations' COMTRADE database, Figure 1 shows that total exports and 'metal and energy' exports of these countries to China broadly move together. Therefore, 'total exports' series should not drive the results.

Data for Canada is extracted from Statistics Canada. Australia data is taken from Reserve Bank of Australia website[8]. For the rest, data comes from Datastream. See appendix for further details regarding specific series used for each country. We use the logarithmic transformation of all series except interest rate.

IV. Results

IV.1. China and US economic activity factors

We start with the factor estimations from the dynamic factor model. Figure 2 panel (a) plots the China economic activity factor and the US economic activity factor along with their 68% error bands. 68% error bands are used as standard error bands in Bayesian literature, which is equivalent to one standard deviation error around the median. The factors are tightly estimated. In figure 2 panel (b), both factors are plotted in one graph. We find that China factor is more volatile than the US factor. We also note that the post 2008 recovery is quicker for China factor as compared to the US factor, possibly due to the stimulus investment spending undertaken by the Chinese government in 2009. The two panels of figure 3 show that the estimated factors are

[8] Industrial production and CPI data for Australia are quarterly and have been converted to monthly frequency using Chow-Lin estimator on EViews.

highly correlated with their respective industrial production indices. So, we see that the estimated factors are, in fact, two separate and independent factors broadly consistent with the macroeconomic trends of the corresponding countries. The IP series are somewhat noisier and more volatile than the factors, consistent with our view that adding more indicators improves our estimate of the underlying state of the economy.

IV.2. Effect of domestic China shock

We now assess the effect of a negative shock to the Chinese economic activity on the economies of commodity exporters. For this purpose, we present the impulse response of each variable of a commodity exporting country to one unit shock to the China factor using our FAVAR model. We also show the results for US shock, alongside, for comparison purpose. Each country FAVAR includes three lags of endogenous variables and four lags of latent factors[9]. All results are based on recursive ordering of the variables during estimation. We report the posterior median and 68% error bands of the impulse responses, as is common in the Bayesian literature. The response horizon is twelve months.

The baseline five-variable FAVAR answers the question: whether China shock (or US shock) has any effect on the macroeconomic variables of a commodity exporting country. The baseline macro and financial variables are: output, price level, interest rate, USD exchange rate and stock market index.

We are also interested in investigating the channels through which these effects take place. This is done by expanding our baseline FAVAR and including variables which denote possible transmission channels. We assess two such channels —commodity price channel and export channel. For these countries, an increase in the global price of their export commodity acts as terms of trade improvement. So, we could also think of the price channel as ToT channel. As China buys more commodities, the exports of these countries rise. We term it as ‘export channel’ through which China affects these countries. We expand our baseline five-variable FAVAR system to a seven-variable FAVAR by adding variables – ‘global commodity price’ and ‘export to China’. The endogenous variables are ordered as follows: commodity price, output, price level, interest rate,

[9] We also looked at the suggested number of lags of endogenous variables using AIC criterion. The suggested number is different for different countries. In order to maintain uniformity, we use same number of lags for all countries. The results are broadly unchanged when we use the number of lags suggested by AIC.

export to China, USD exchange rate and stock market index. The expanded FAVAR helps us estimate the effect of a shock to the economic activity of China and the United States on the global commodity prices. Along with this, we derive inference on whether the two channels discussed above are important in facilitating shock transmission for a given country. We also check robustness of our results by ordering commodity price after the macroeconomic variables (output and price) of commodity exporting countries to allow for macroeconomy of these countries to affect commodity price. These results are reported in the robustness checks section as RC7.

Now we illustrate the impulse responses to China shock and US shock using the results for Russia. After that we will discuss the effect on all countries in relative terms.

IV.2.1 Impulse Responses of Russian economy to China shock and US shock

Figure 4 panel (a) reports the impulse responses of the Russian variables to a negative unit shock to the Chinese economic activity factor, using the baseline five-variable FAVAR. Russian IP starts falling as soon as the shock hits. It reaches the trough in the seventh month of forecast at around 200 basis points (bp) and continues to fall throughout the forecast horizon. There is a temporary fall in price level. Russian Ruble depreciates and stock market collapses. Exchange rate depreciation starts at around 60 bp and continues vigorously after that to reach about 400 bp by the seventh month. As will be seen later, Russia, in fact, sees the highest depreciation among the sample countries in response to the China shock. The interest rate rises, possibly because the central bank intervenes to save further fall of the Ruble. In the first month, stock market is down by 550 bp. The trough effect is about thrice as large, and occurs after 4 months. Panel (b) shows the impulse responses to a negative unit shock to the US factor. US shock has smaller effect on Russia as compared to China shock. The trough effect on Russian IP is about three-fourth and on stock market is about one-third that of China shock. Interest rate rises and exchange rate depreciates but the effects are not significant. The Russian stock market reacts more quickly to China shock than to US shock.

Figure 5 panel (a) presents the impulse responses of global oil price and all Russia variables to a one unit adverse shock in the Chinese economic activity factor, using expanded seven-variable FAVAR. As one would expect, the error bands of these impulse responses are wider than that those for baseline FAVAR, as degrees of freedom is smaller. Nevertheless, it provides significant and useful inferences. In response to the shock, oil price and exports to China fall during the forecast period and reach their trough at about 1200 bp lower than pre-shock level. Panel (b) shows the effect of a US factor shock. Oil price decreases and the trough effect of US shock is about 700 bp. We also find that Russian exports to US reduce in response to the US shock. Therefore, we see that both China and US shock are transmitted into Russian economy through both commodity price channel and direct trade channel.

In both panels (a) and (b), we find that some of the variables, which had significant effect in the baseline model (Figure 4), show less or no significant response to the shock, in the expanded system. This is the result of capturing adequately the channels through which the shock had an effect on these variables. Since there is no other way the shock can affect these variables, effect of the shock itself becomes insignificant. Let us take the impulse responses to China shock, for example. Exchange rates showed highly significant response in the baseline model, whereas in the expanded model it becomes more or less insignificant. So, our model suggests that the response of Russia's currency exchange rate movements to China shock (in the baseline model) was actually a response to global oil price movements (and/or change in its ‘exports to China’) caused by the China shock. So, after incorporating the commodity price channel (and the export channel) in the model, there is no extra effect of the shock on Russian exchange rate. Also, the reduced degrees of freedom make some responses insignificant.

IV.2.2 Effect of China shock on all commodity exporters

For the rest of the countries we present a summary of impulse responses using tables. Tables 1 and 3 show impulse responses of all countries to a negative China shock using the baseline FAVAR and expanded FAVAR, respectively. Tables 2 and 4 show the corresponding estimates for a negative US shock. In all four tables, panel (a) shows the months in which a shock had significant effect, and panel (b) shows the month in which the trough occurred and its magnitude. Along with these, we also present table 5 and figure 6, which we refer to when we discuss the results. Table 5 displays the net commodity exports to world of each country in the sample as a percent of its total exports and GDP. Figure 6 exhibits the share of commodity exports to

China and to the world, as a percent of a country's GDP. The countries in our sample are: Australia, Brazil, Canada, Chile, Colombia, Malaysia, Mexico, Peru, Russia and South Africa.

As seen in the case of Russia, with a negative shock to the Chinese economic activity factor, output decreases, currency depreciates and stock market falls in a commodity exporting country. Effect on price level and interest rate is more dispersed. Only five out of the ten countries in the sample undergo fall in price level after a China shock. Monetary authorities are seen to react in various ways, with some increasing interest rate while others decreasing it or keeping it stable in response to the shock. Since, price level and interest rate do not show any consistent and interesting dynamics, we treat them more as controls in our model and do not discuss them much going forward. Results for these two variables have been presented for the baseline FAVAR, in tables 1 and 2. We do not report the estimates for these for the expanded FAVAR model and for all robustness checks in order to save space. All results are available upon request.

Our results are quite similar to those of Gauvin and Rebillard (2015), henceforth GR, which studies the effect of China's hard landing on 36 developed and developing countries using a global VAR (GVAR) framework. A global VAR framework is especially helpful when one is trying to understand the international transmission of a global or country-specific shock through all possible channels. Our focus, however, is to explore specifically the commodity market channel and also to take care of the data quality issue of the Chinese data. FAVAR is suitable for both these purposes and hence, we go for this framework. Our study should be seen as a complement to GR and other similar works, contributing to this growing literature to arrive at more certain and reliable inferences about China's impact on the global commodity market.

In terms of the effect of China shock on an economy, we do not find stark dissimilarities between oil exporters and metal exporters. As can be seen from panels (a) and (b) of Table 1, the countries which lose the most, in terms of reduced output, are Brazil, Russia and Peru. Mexico emerges quite resilient. Advanced economies are less affected by China shock as compared to emerging economies- Canada sees no effect and Australia faces small effects.

Examining the countries in Latin America, we find that Brazil and Peru are among the worst hit, in terms of industrial production. Both Peru and Chile are copper exporters. Despite Chile's heavy reliance on copper exports as shown in figure 6 and table 5, we find that the negative China shock has a smaller effect on its IP than on the IP of Peru. This could be ascribed to its strong policy framework, particularly its very flexible exchange rate, which cushions the fall in demand so that the output is stabilized to some extent, with a substantial depreciation. Chile[10] is also the only country in our sample to have just one month effect of the shock on its stock market. On the other hand, Peru's partially dollarized economy does not allow its central bankers to let the exchange rate freely absorb the effect of the shock. Table 1b shows that in response to China shock, Chilean Peso depreciates much more than Peruvian Sol.

The strong effect of the shock on Brazil is rather surprising[11], given that its metal exports constitute a relatively small part of its GDP (see figure 6 and table 5). GR also finds a similar result for Brazil and attribute the strong effect of China as a 'neighborhood effect' transmitted into the Brazilian economy through its biggest Latin American importer, Argentina. World Bank (2015) and GR find that Argentina is highly vulnerable to a decline in China's growth. We estimate the effect of China shock on Argentine economy using our baseline FAVAR and confirm this finding[12]. The results are presented in panels (a) and (b) of table 1.The magnitude of effect on Argentina's IP is comparable to that of Brazil.

Mexico faces smaller output loss than other Latin American countries due to its limited net export of oil (table 5) and minimal direct oil trade exposure to China (figure 5). Its strong trade linkage with the United States, a relatively less open economy and net commodity importer, also helps. Heavy reliance on oil export, as shown in table 5, leads Colombia to incur significant output loss from the oil price fall caused by the shock.

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[10] In the FAVAR for Chile we add an earthquake dummy for March 2010. The earthquake occurred on February 27, 2010.

[11] Since year 2013, Brazil has been entangled in a domestic political crisis which has been blamed for the poor performance of the economy over the last two years. Since the period coincides with the time of China's slowdown, we perform a model validation test by adding a political crisis dummy to the model and also replacing the Lehman crisis dummy with a US 2007-09 recession dummy. The political crisis dummy takes value 1 for all months from June 2013 onwards. The impulse responses from our main model are robust to these controls.

[12] The data for Argentina is also obtained from Datastream. In the Argentina model, we add dummy for the Argentina sovereign default crisis period. Industrial production and CPI data for Argentina are quarterly and have been converted to monthly frequency using Chow-Lin estimator on EViews.

With the highest dependence on commodity exports in our sample, as can be seen in table 5 and figure 6, it is no surprise that Russia is one of the countries, most severely affected by China shock. Although less affected than Russia, South Africa is also hit hard by the shock due to fall in metal prices. Their highly flexible exchange rates limit further output loss by allowing them the maximum depreciation among all countries.

Next, we discuss the case of Malaysia. Despite being a highly open economy and China being its biggest trading partner, Table 1 panel (b) ('Trough effect') shows that the effect of a negative shock to the Chinese economy is relatively mild on Malaysia's output compared to those of big commodity exporters. There could be at least three reasons for this result. The recent slowdown in Chinese GDP has been associated with a slowdown in its investment spending. As Malaysia is an oil exporter, the expected effect of this slowdown should be relatively less through the direct trade channel because oil demand is driven more by consumption than investment. Secondly, although the falling oil price should be damaging for Malaysia, but its relatively smaller net oil export (see table 5) limits this loss.

Third, and perhaps the most important, reason is the type of goods, other than oil, Malaysia exports to China. Malaysia is an important trade partner of China in its global value chain of production, which is driven by the demand for Chinese exports. So, although Malaysia exports massively to China, a large part of these exports are intermediate goods which are processed further in China for re-exporting, mostly to developed countries. Therefore, Chinese demand for Malaysian exports includes a substantial hidden (final) demand from these developed economies. Figure 7 shows the 'ratio of value-added (exported directly, and indirectly through other countries) to China towards its final demand' to 'gross exports to China', for all countries in our sample for which data is available in OECD-WTO Trade in Value-Added database. It shows that 20% of Malaysia's gross exports to China are not consumed in China. Our China factor has been extracted in a manner such that it is representative of China's domestic economy and eliminates the external effects. This is the reason we find smaller effect of China on Malaysia as compared to other studies like GR, which uses China GDP growth as the variable in their GVAR model to derive China shock. As a robustness check when we replace the China factor with China IP growth and then compute the effect of the shock to this growth variable, we find the effect on Malaysian IP to be higher.

A surprising observation from figure 7 is that less than 60% of what Chile exports to China is actually consumed in China. This might be an additional reason for relatively lower effect on China shock on Chile. Exploring this channel would be an interesting exercise but is beyond the scope of this paper. So, we leave it to future research.

Table 2 shows that a negative US shock leads to output reduction in all countries in our sample, whereas China shock affected only a subset of countries (Table 1). Except Chile, all countries' stock markets fall in response to negative US shock. Comparing panel (a) of tables 1 and 2, we find that stock markets of most countries respond more quickly to China shock than to US shock. Further, comparing panel (b) of these tables we find that for many countries stock market response is stronger for China shock than to US shock. A closer examination of these countries, as shown in Table 2c, suggests that countries with bigger share of net commodity exports in their GDP tend to be more responsive to China shock.

IV.2.3 Shock transmission channels

Our model facilitates examining two main channels of transmission of China shock into commodity exporting economies – commodity price channel and direct trade channel- along with currency exchange rate which acts as a shock absorber. Table 3 panel (b) shows that a negative shock to the Chinese demand causes both metal and oil prices to fall. We find that the fall in oil price is about 1.5 times the fall in metal price. This is in line with GR, who suggest that oil price is more sensitive to demand shock than metal price. A parallel analysis for negative US shock, as shown in panel (b) of table 4, gives us a similar effect on the commodity prices. We find that for commodity prices the effect of China shock is more persistent than that of US shock. The effect of both shocks is stronger for oil than for metal prices.

Direct trade linkage, through 'export to China', is less important as a shock transmission channel. Figure 5 shows each country's energy and metal exports to China and the world, in percent of its GDP. We show oil exports for oil exporters and metal exports for metal exporters. Oil export to China of countries located far from China, in our sample- Canada, Colombia and Mexico- is trivial. Therefore, this transmission channel is not active for these countries. This is also observed in our results in panel (b) of Table 3. For energy exporters located close to China and metal exporters, we do see significant export effect but only for a few months. Although Brazil and Russia show immense fall in their export to China, their commodity export to China is very low relative to their respective GDPs, which makes the channel less important. South Africa is a metal exporter but it sees significant reduction in its export to China for only one month, possibly because a significant part of its commodity export consists of gold. The factors determining the demand for gold and iron-ore are quite different. Peru also shows decrease in export to China for only one month after the shock. This result is also supported by Han (2014), who finds that spillovers from China occur mainly through the commodity price channel for Peru, rather than direct trade linkage.

Finally, exchange rate depreciation reduces the effect of commodity price fall on export and output of countries with flexible exchange rate. This is observed in our sample for all commodity exporters except Colombia (see table 1 panel (a)).

In tables 3(a) and 3(b), we see that in the expanded model with China shock, the fall in industrial production is significant for fewer countries. Mexico now shows no significant effect and, for Colombia and Malaysia the effect lasts only one period. This implies that the included transmission channels are adequate in order to explain how China shock affects these two countries. For other countries, additional channels are important as well. In their GVAR set up, GR estimate the 'neighborhood effect' and 'investment effect' of China shock to be significant. Neighborhood effect occurs when a China shock hits a country and the country's export partner, which is also a commodity exporter. Investment effect pertains to reduction in the long-term investment spending in the mining and extractive sectors as commodity price falls and demand slows.

V. Robustness Check

In this section we describe the series of robustness exercises that we have undertaken. The checks have been performed for both baseline and expanded FAVAR for all countries. Table 6 shows the impulse responses to negative China shock for each of the robustness test performed, using our baseline 5-variable FAVAR. Since factor identification is an important aspect of our paper, we devote a series of robustness checks to show that our results are not sensitive to a particular model specification of the dynamic factor model. We show four sets of results using four different China factor estimates.

In the first set of checks, we tested the sensitivity of the China and US factor estimations and thereby, of the sensitivity of the effect of shocks to these factors, to changing the combinations of series taken as input in the dynamic factor model. We tested out several combinations, some using macroeconomic series not included in the main model. The results are effectively similar. We show the model results using two such alternate variable combinations in the dynamic factor model. So, in our first two factor estimates, we change the combination of US and China variables used as input in the dynamic factor model. In the first factor estimate for robustness [RC1], we use the same set of US variables as in the main model. For China we use only a subset of variables including – a) industrial production index, b) electricity production, c) retail sales and d) floor space started: commodity building. In the second China factor estimate [RC2] we use the same China variables as the main model. For US we include 5 additional variables: 1) non-manufacturing business activity index, 2) housing starts: new privately owned, 3) index of aggregate weekly payrolls of production and non-supervisory employees- total private, 4) motor vehicle retail sales- domestic autos; and 5) real retail and food service sales. Table 6 shows that the results for 'period of significant effect' and 'trough effect period' for RC1 and RC2 are very similar to those in the 'Main Model'. We find that the magnitude of effect generally varies across models. However, the ranking of countries remains broadly similar. Therefore, all inferences in the robustness section are based on these rankings rather than the actual magnitude of effect. In their study, GR also emphasize the order of magnitude, rather than precise estimates, when discussing their results.

In our dynamic factor model we make an assumption for the purpose of factor identification that US factor affects all variables whereas China factor affects only the Chinese variables in the system. With China's share in world GDP rising and the world economy becoming more integrated, this assumption might come across as somewhat restrictive. So, the third China factor estimate [RC3] is derived from a dynamic factor model in which we allow China factor to affect US variables with a lag. Table 6 shows that, as in the case of RC1 and RC2, RC3 produces results very similar to those of the main model.

Most previous studies (Kose et al., 2008; Chatterjee, 2016) deriving global and regional factors have used quarterly data and they include one lag of factors and errors in their model. For the ease of computation we also include one lag of factors and errors in our model although our data is monthly. Therefore, we conduct a robustness check [RC4] by allowing three lags of factors and errors in our dynamic factor model, which would be equivalent to previous studies' assumption of one lag for quarterly data. Table 6 shows that, except for Malaysia's output, our main model results are robust to this addition of lags in the dynamic factor model for all countries and variables.

We also show a set of impulse responses to China shock in a model in which we replace the China factor with the actual growth rate of Chinese IP [RC5]. As table 6 shows, the results are robust. Figure 8 panels (a) and (b) show the impulse responses of Russian macroeconomic variables to a unit shock to China IP growth in baseline FAVAR and expanded FAVAR, respectively. The magnitude of the effect of China shock, on all variables, is smaller than when we use China factor. The relative ranking of countries, in terms of output effect, is largely similar to our main model[13].

Table 7 shows the above robustness checks for the expanded FAVAR models. We find that main model results are robust for most countries and variables. Some countries which yield less robust results are the ones which had relatively lower effect of China shock in the main model, for example Mexico, Malaysia and South Africa have less robust output effect.

In addition to the robustness check of the latent China factor, we also perform robustness check of the FAVAR estimations. We show two sets of results in this regard. In the first one [RC6], when we perform FAVAR, instead of including 3 lags of endogenous variables for all countries, we include the AIC criterion suggested number of lags for each country. Ivanov and Killian (2005) suggest using AIC criterion for monthly data. Table 6 shows that our baseline model results are robust. Again, we find that some countries which do not show robust results are the ones which had lower effect of China shock in our main model. Table 6 shows that Australia and Mexico, which have AIC suggested lags as 6 and 7 respectively, have less robust output effect. In the expanded FAVAR we find that using AIC suggested lags for some countries, especially when they are

[13] Malaysia moves up the ranking for the reasons discussed in the Results section.

much higher than 3, creates unstable dynamics in the system. Therefore, for these countries we use the SC criterion suggested number of lags instead, which is generally smaller. Table 7 shows that the expanded FAVAR results are robust. For Australia[14] and Mexico we use one lag. This is SC suggested number of lags for Mexico.

The second robustness check [RC7] is performed for the expanded seven-variable FAVAR. In this, we show that our results are not sensitive to changing the order of the variables while taking recursive restrictions. We use the following variable ordering: output, price level, interest rate, commodity price, exports to China, USD exchange rate and a stock market index. We have moved commodity price from the first place to the fourth place to allow events in a country to affect the global price of their export commodity. Table 7 shows that our expanded FAVAR results are robust to this check. More importantly, the effect on commodity prices and 'exports to China' are robust, which is our center of interest in the expanded FAVAR model.

Table 8 shows the relative ranking of the countries, in term of output effect of China shock, within each model. The table shows that the rankings of the countries are quite consistent across models. We can broadly group countries in 3 categories. Most affected countries are Brazil, Russia and Peru. Least affected countries are Australia, Canada, Chile and Mexico and; countries with intermediate effect are South Africa, Malaysia and Colombia.

VI. Conclusion

The reduction in global commodity prices during the last four years has created turmoil for many commodity exporting countries. Some have already gone into recession. Some countries are grappling with low growth rates. The slowdown in investment spending by the Chinese government has been cited as an important cause for this price slump. Our paper contributes to this discussion by examining empirically whether and how does a domestic shock in China affects the macroeconomy of a commodity exporting country. We assess the role of two important channels of shock transmission- commodity price and exports. A positive shock in the Chinese economy raises its demand for commodities which, in turn, increases their global prices. This is a positive

[14] For Australia, AIC suggested number of lags is 8 and SC suggested is 2. But both give unstable dynamics. So, we are using only one lag.

terms of trade shock for a commodity exporter. The increase in demand also causes increase in its exports to China, which is the second channel of transmission.

We deploy a factor augmented vector autoregression (FAVAR) model to assess the China effect. This is carried out in two steps. First, we use a dynamic factor model to derive a latent factor representing Chinese economic activity. In the second step, we perform a vector autoregression (VAR) for a commodity exporting country in which the latent China factor enters as an exogenous variable. Along with China factor, we also derive a global economic activity factor (for simplicity we use US factor) and assess its effect on commodity exporting countries to examine China's relative importance in the world economy.

We examine ten commodity exporters: Australia, Brazil, Canada, Chile, Colombia, Malaysia, Mexico, Peru, Russia and South Africa. A negative China shock causes output loss and stock market fall in these countries. US shock affects output of all countries but China shock affects only a subset of countries. Stock markets of countries with heavy dependence on commodity exports tend to react more quickly and strongly to China shock than to US shock. The countries worst hit, in terms of industrial production, by an adverse China shock are Brazil, Russia and Peru. Emerging economies are affected more as compared to advanced countries.

Commodity price emerges as the main channel of China shock transmission. A negative shock to Chinese demand causes both metal and oil prices to fall. Both China and the US domestic shocks have about 1.5 times the effect on oil price as compared to metal price. For commodity price, China shock has more persistent effect than US shock. Exports to China also fall for countries which export large amounts to China. However, the effects last only a few months and so the long term effect is small. Exchange rate adjustment is another channel of the shock transmission. Countries with flexible exchange rates benefit by letting their currency depreciate to cushion the fall in demand resulting from the adverse external shock.

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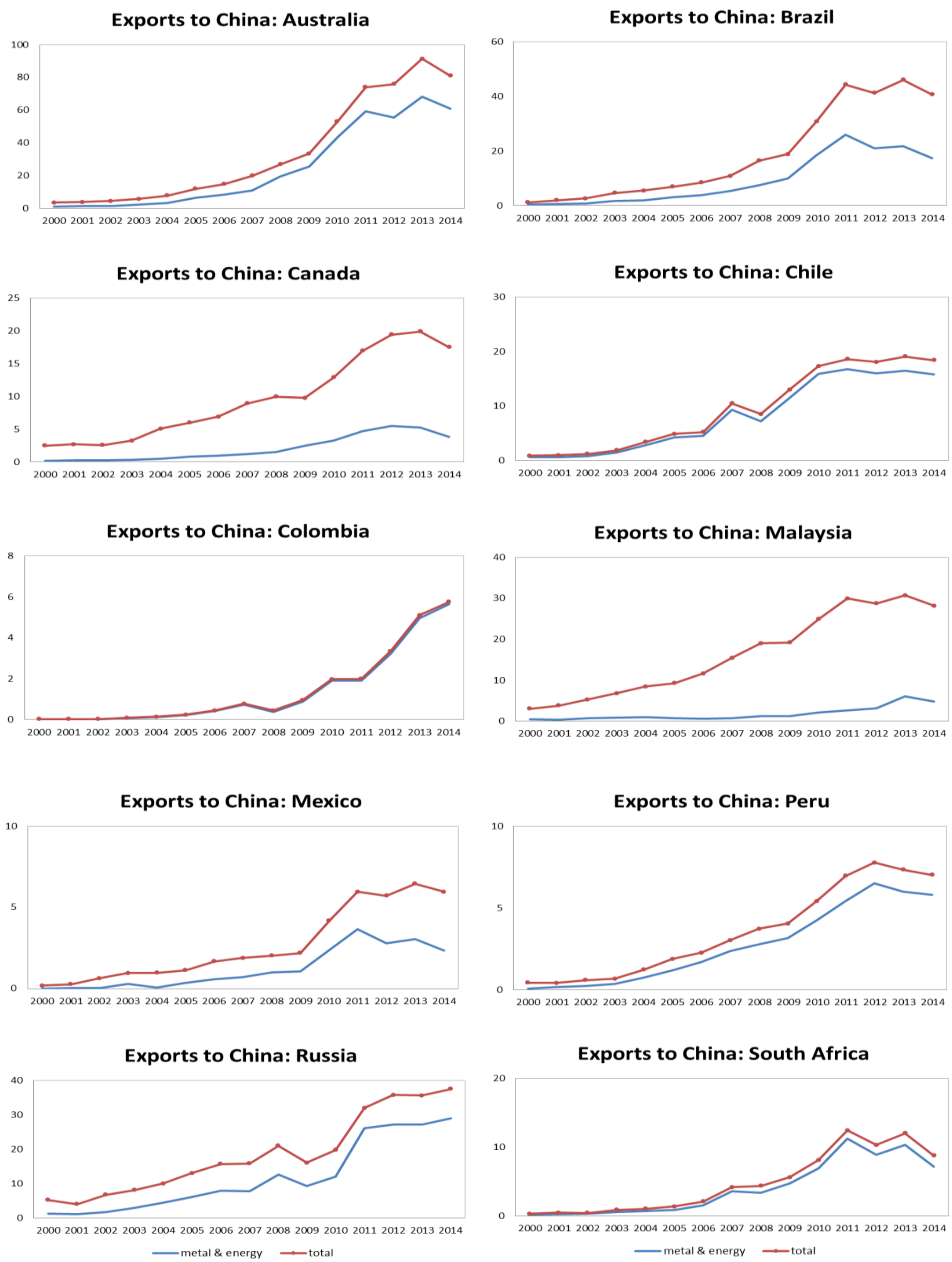
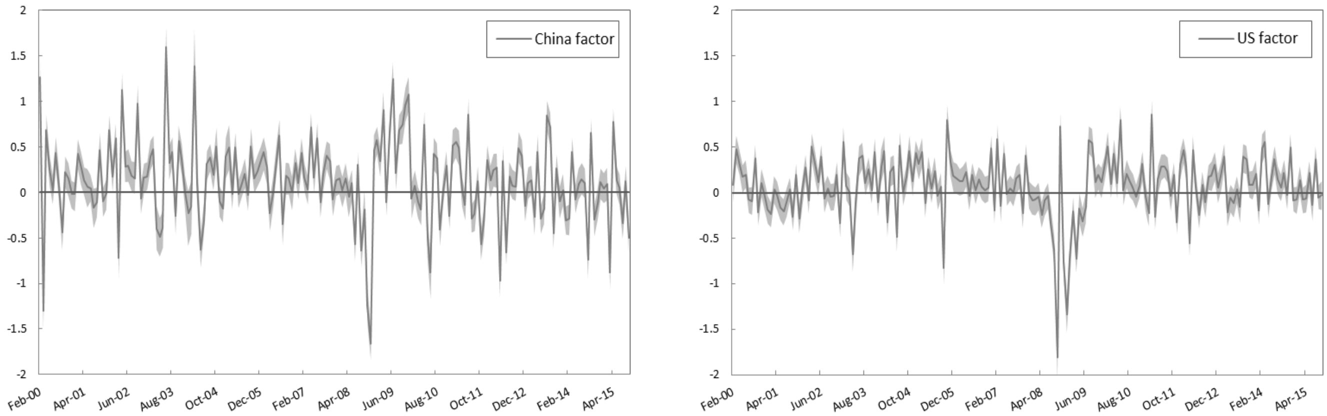
Figure 1: Exports to China (in current billion USD)



Note: The commodity export data is taken from COMTRADE. We use the HS classifications 26, 28, 72, 74 and 2502 for metals, and 27 for energy. The total export data is taken from DOTS.

Figure 2: China and US Economic Activity factors

Panel (a)



Panel (b)

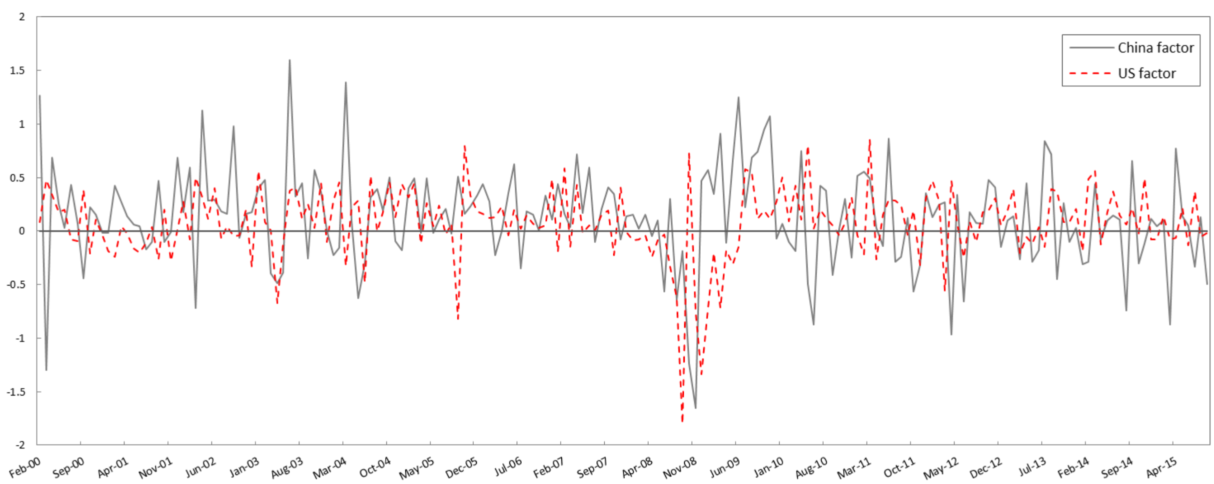


Figure 3 (a): China Economic Activity Factor

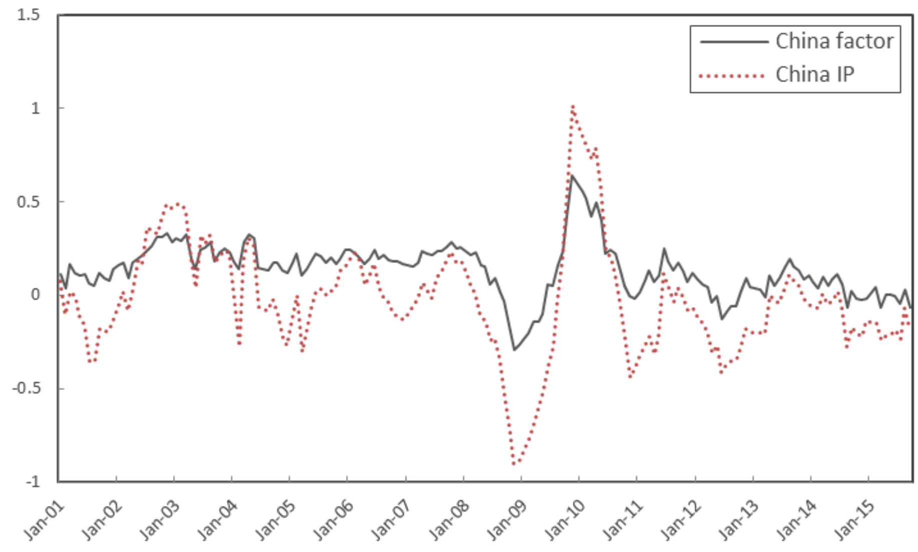
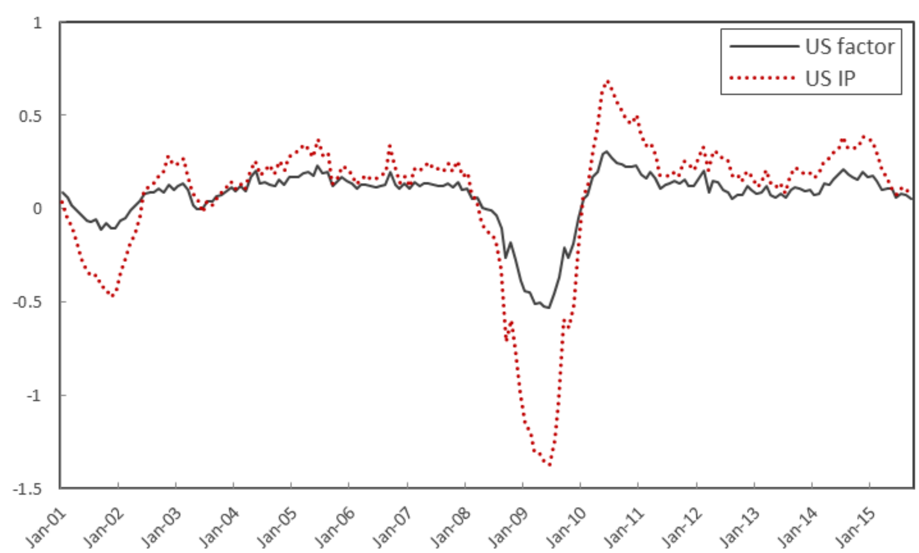


Figure 3 (b): US Economic Activity Factor



Note: The economic activity factors have been extracted using a broad set of economic indicators. The solid line represents the economic activity factor and the dotted line depicts the growth of industrial production for comparison. For all series, we take the twelve-month moving average.

Figure 4 (a): Baseline FAVAR Model Impulse Responses to China Factor Shock: Russia

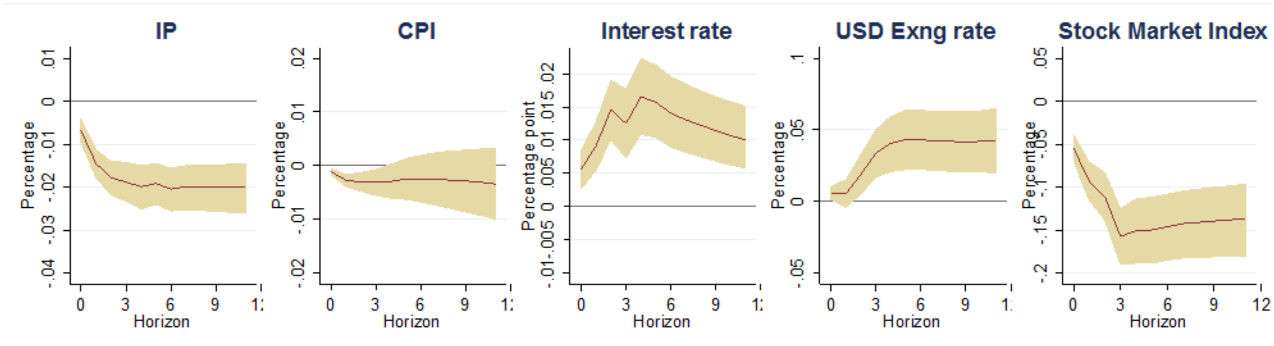


Figure 4 (b): Baseline FAVAR Model Impulse Responses to US Factor Shock: Russia

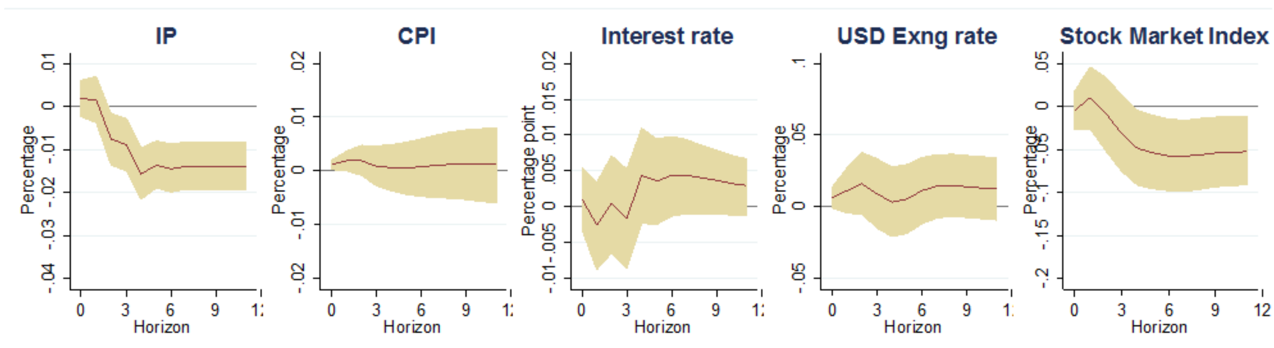


Figure 5 (a): Expanded FAVAR Model Impulse Responses to China Factor shock: Russia

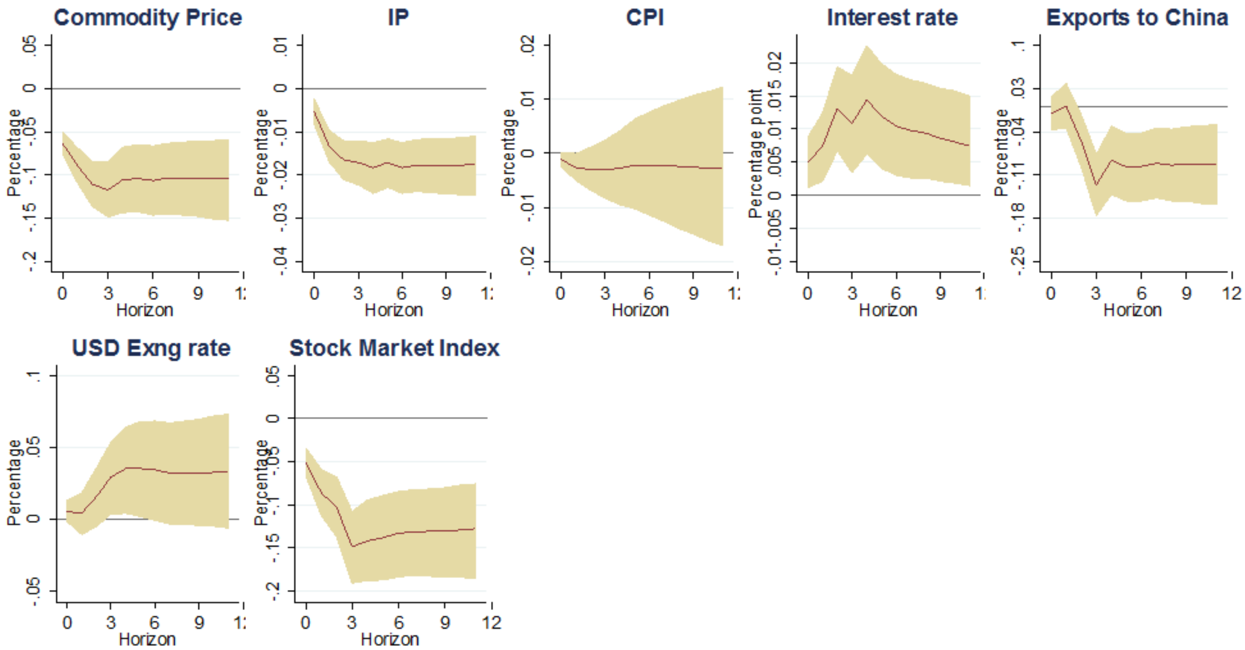


Figure 5 (b): Expanded FAVAR Model Impulse Responses to US Factor shock: Russia

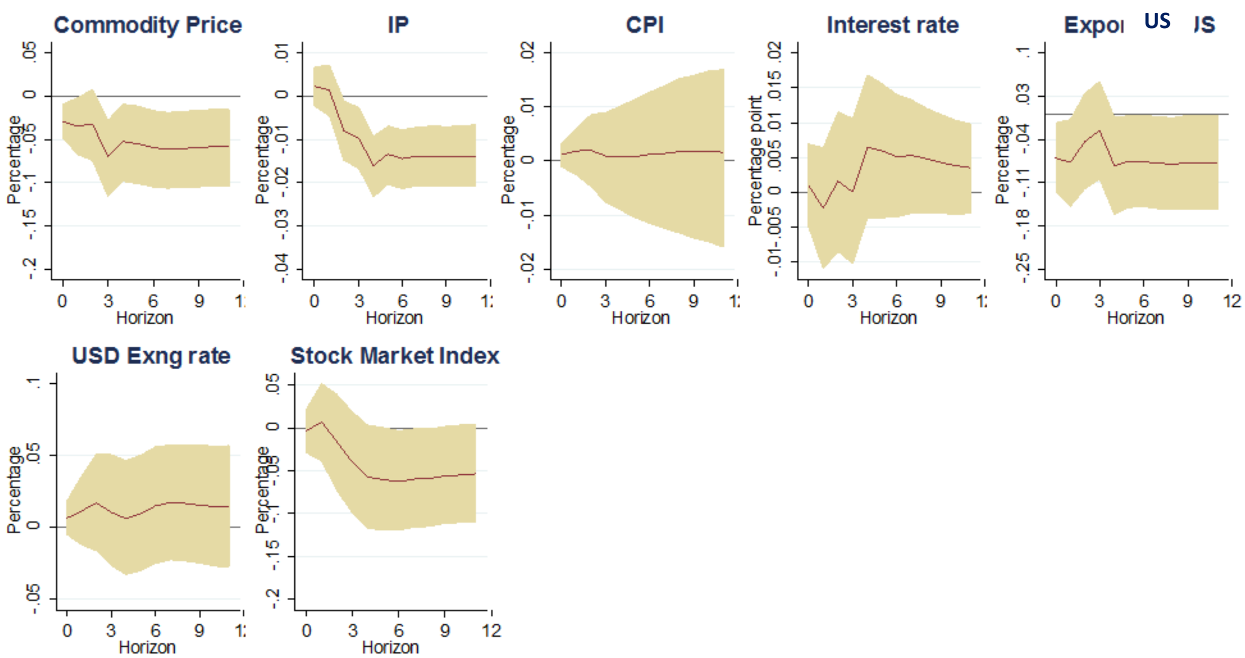
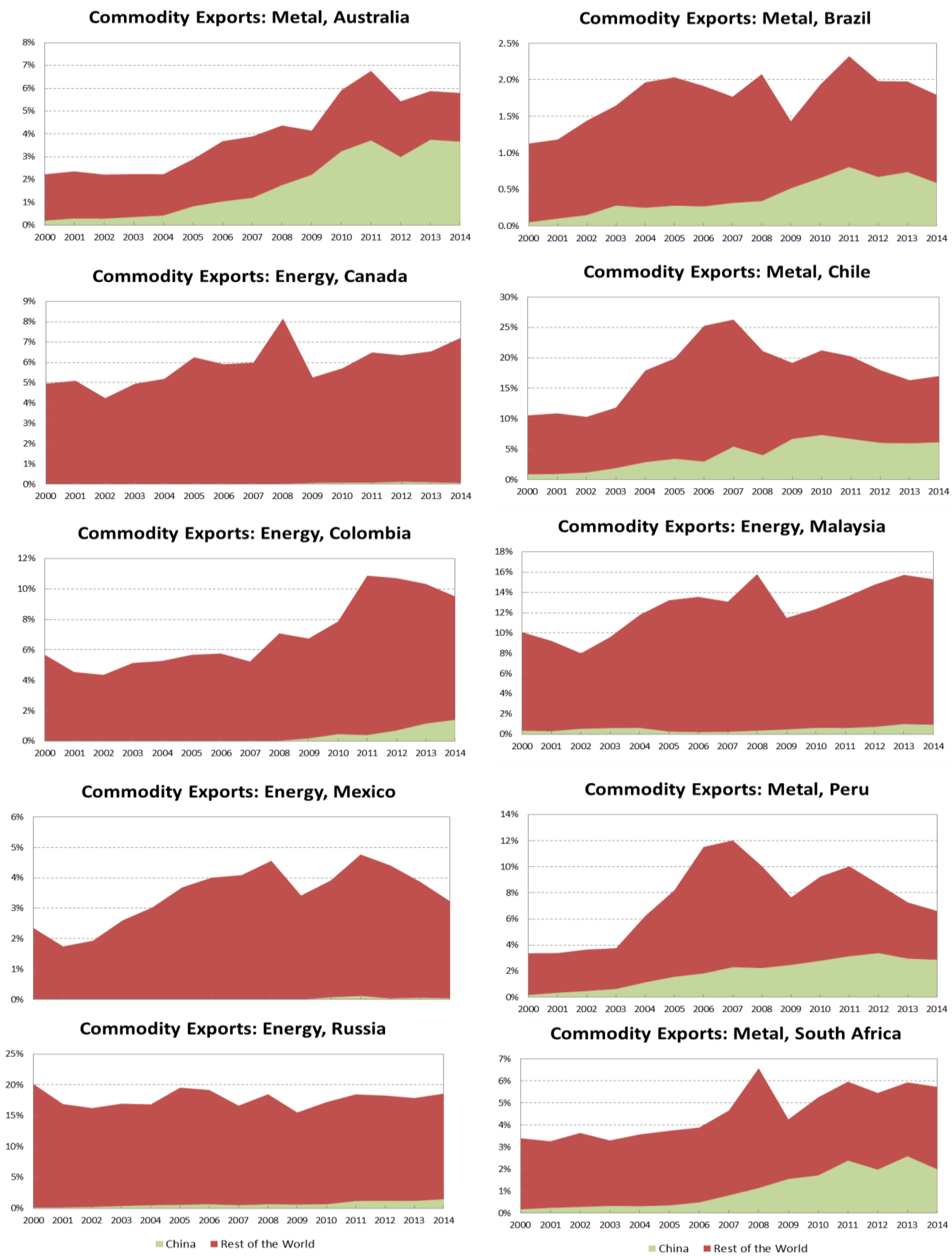
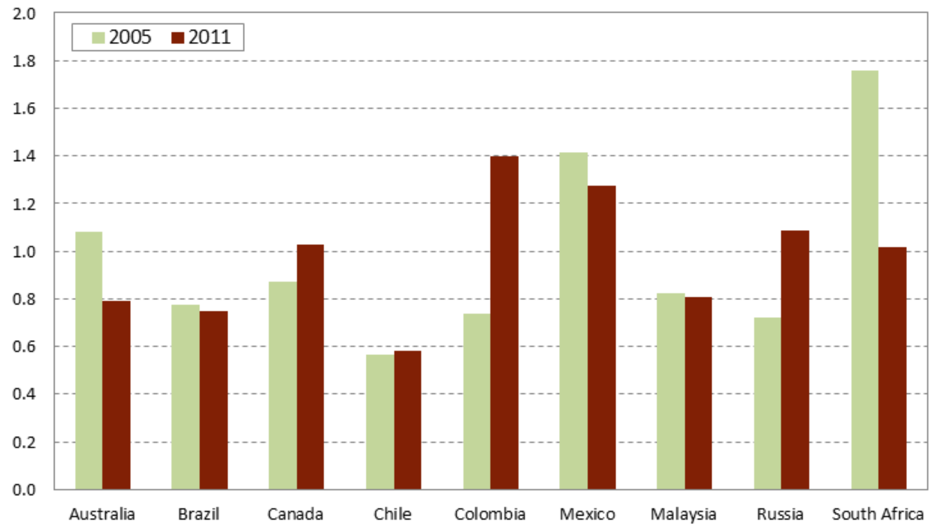


Figure 6: Share of China in Total Commodity Exports (%GDP)



Note: The data is taken from COMTRADE. We use the HS classifications 26, 28, 72, 74 and 2502 for metals, and 27 for energy.

Figure 7: Ratio of 'Value-added towards China's Final Demand' to 'Gross Exports to China"



Source: OECD-WTO Trade in Value-Added and IMF DOTS

Figure 8 (a): Baseline FAVAR Model Impulse Responses to China IP growth Shock: Russia

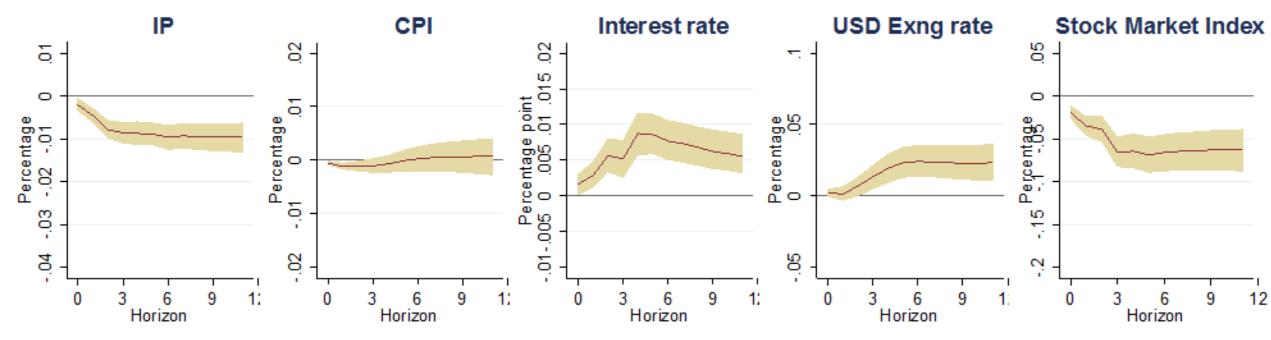


Figure 8 (b): Expanded FAVAR Model Impulse Responses to China IP growth Shock: Russia

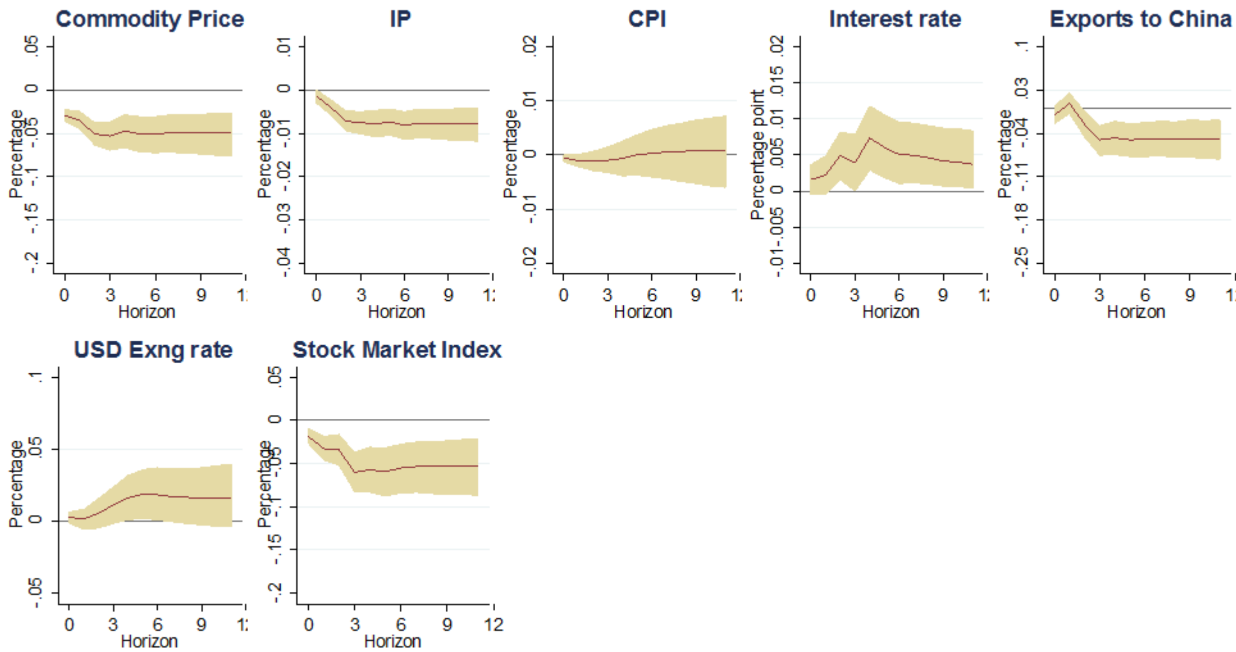


Table 1a: Periods in which China Shock has Significant Effect: Baseline Model

Country	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index
Argentina	1 to 12		7 to 12		1 to 12
Australia	5 to 12	4 to 12	2 to 12	1 to 12	1 to 12
Brazil	2 to 12	3 to 12	6 to 12	1 to 1	1 to 12
Canada		3 to 12		1 to 12	1 to 12
Chile	1 to 1		2 to 12	1 to 5	1 to 1
Colombia	1 to 12		1 to 11		1 to 12
Malaysia	2 to 6		1 to 3	1 to 12	1 to 12
Mexico	5 to 12		1 to 3	1 to 12	1 to 12
Peru	1 to 12			1 to 12	1 to 12
Russia	1 to 12	1 to 4	1 to 12	1 to 12	1 to 12
South Africa	1 to 12	1 to 12		1 to 12	1 to 6

Table 1b: Trough Effect and Trough Period of China Shock Effect: Baseline Model

	Trough Period					Trough Effect				
Country	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index
Argentina	8		9		4	183 bp		216 bp(+)		1450 bp
Australia	9	8	9	5	5	50 bp	40 bp	19 bp(-)	261 bp	511 bp
Brazil	5	12	12	5	4	244 bp	87 bp	55 bp(-)	157 bp	790 bp
Canada		5		6	12		14 bp		293 bp	484 bp
Chile	1		6	3	4	78 bp		44 bp(+)	224 bp	171 bp
Colombia	1		12		8	129 bp		30 bp(+)		704 bp
Malaysia	3		3	4	2	105 bp		8 bp(+)	148 bp	403 bp
Mexico	5		3	10	7	41 bp		19 bp(-)	223 bp	443 bp
Peru	5			5	4	166 bp			130 bp	1022 bp
Russia	7	12	5	7	4	204 bp	34 bp	165 bp(+)	434 bp	1574 bp
South Africa	4	12		12	4	113 bp	74 bp		329 bp	374 bp

Table 2a: Periods in which US Shock has Significant Effect: Baseline Model

Country	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index
Australia	1 to 12		2 to 12	1 to 12	4 to 12
Brazil	5 to 12			2 to 6	4 to 7
Canada	1 to 12		4 to 12		3 to 12
Chile	2 to 12	1 to 12	5 to 6		
Colombia	3 to 12		2 to 12	1 to 4	4 to 4
Malaysia	1 to 12	1 to 12	3 to 12	4 to 9	1 to 12
Mexico	1 to 12	1 to 1	3 to 12	2 to 12	3 to 12
Peru	2 to 12			2 to 4	3 to 12
Russia	3 to 12				5 to 12
South Africa	2 to 12			2 to 4	1 to 12

Table 2b: Trough Effect and Trough Period of US Shock Effect: Baseline Model

	Trough Period					Trough Effect				
Country	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index	Industrial Production	Price Level	Interest rate	USD Exchange rate	Stock Market Index
Australia	4		6	3	5	41 bp		48 bp(-)	627 bp	350 bp
Brazil	5			4	4	105 bp			311 bp	417 bp
Canada	5		9		4	220 bp		36 bp(-)		462 bp
Chile	4	12	5			202 bp	55 bp	37 bp(-)		
Colombia	3		12	3	4	132 bp		72 bp(-)	598 bp	400 bp
Malaysia	4	12	4	4	4	205 bp	43 bp	24 bp(-)	164 bp	409 bp
Mexico	5	2	8	3	4	131 bp	11 bp	73 bp(-)	356 bp	521 bp
Peru	4			4	4	165 bp			116 bp	810 bp
Russia	5				8	157 bp				579 bp
South Africa	4			3	4	222 bp			573 bp	413 bp

Table 2c: Trough Effect of China and US Shocks on Stock Market: Baseline Model

Country	Net Commodity* Export (%GDP)	China shock	US shock
Russia	19.3%	1574 bp	579 bp
Chile	11.2%	171 bp	
Colombia	6.1%	704 bp	400 bp
Australia	5.6%	511 bp	350 bp
Peru	5.5%	1022 bp	810 bp
Canada	3.7%	484 bp	462 bp
Malaysia	3.4%	403 bp	409 bp
South Africa	1.6%	374 bp	413 bp
Mexico	1.3%	443 bp	521 bp
Brazil	0.7%	790 bp	417 bp

*Commodity includes Metals and Energy

Table 3a: Periods in which China Shock has Significant Effect: Expanded Model

Country	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price
Australia	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12
Brazil	2 to 12	2 to 12		2 to 6	2 to 12
Canada			1 to 6	1 to 7	1 to 12
Chile	1 to 1	1 to 6	2 to 3		1 to 12
Colombia	1 to 1			1 to 8	1 to 10
Malaysia	2 to 3	1 to 12	1 to 4	1 to 5	1 to 12
Mexico			1 to 3	1 to 12	1 to 12
Peru	1 to 12	1 to 3		1 to 12	1 to 12
Russia	1 to 12	3 to 12	4 to 6	1 to 12	1 to 12
South Africa	1 to 10	2 to 3	2 to 3	1 to 4	2 to 12

Table 3b: Trough Effect and Trough Period of China Shock Effect: Expanded Model

	Trough Period					Trough Effect				
Country	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price
Australia	12	2	5	5	5	56 bp	883 bp	299 bp	548 bp	715 bp
Brazil	5	4		4	5	224 bp	1639 bp		609 bp	572 bp
Canada			5	7	4			260 bp	422 bp	1101 bp
Chile	1	3	3		6	77 bp	1025 bp	248 bp		783 bp
Colombia	1			8	4	113 bp			623 bp	895 bp
Malaysia	3	3	4	2	4	96 bp	1049 bp	131 bp	372 bp	1129 bp
Mexico			6	7	4			204 bp	493 bp	1029 bp
Peru	5	1		4	6	154 bp	871 bp		899 bp	803 bp
Russia	7	4	6	4	4	184 bp	1269 bp	354 bp	1486 bp	1174 bp
South Africa	4	3	6	4	5	96 bp	892 bp	297 bp	233 bp	667 bp

Table 4a: Periods in which US Shock has Significant Effect: Expanded Model

Country	Industrial Production	Exports to US	USD Exchange rate	Stock Market Index	Commodity Price
Australia	4 to 11	1 to 2	2 to 4	1 to 12	1 to 12
Brazil	5 to 6	2 to 12		4 to 4	2 to 6
Canada	1 to 12	1 to 12		3 to 4	1 to 12
Chile	2 to 12	3 to 12			
Colombia	3 to 6		1 to 4	4 to 4	1 to 5
Malaysia	1 to 10	1 to 6	4 to 4	1 to 4	1 to 8
Mexico	2 to 10	1 to 9	2 to 4	3 to 4	1 to 12
Peru	2 to 12	1 to 12	4 to 4	3 to 8	3 to 7
Russia	3 to 12	1 to 12		7 to 9	1 to 12
South Africa	3 to 12	2 to 12	2 to 4	3 to 4	2 to 6

Table 4b: Trough Effect and Trough Period of US Shock Effect: Expanded Model

	Trough Period					Trough Effect				
Country	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to US	USD Exchange rate	Stock Market Index	Commodity Price
Australia	5	2	3	5	3	35 bp	432 bp	402 bp	268 bp	637 bp
Brazil	5	2		4	3	94 bp	905 bp		437 bp	680 bp
Canada	5	5		4	4	221 bp	687 bp		471 bp	921 bp
Chile	4	3				203 bp	751 bp			
Colombia	3		3	4	4	134 bp		586 bp	434 bp	1021 bp
Malaysia	4	3	4	4	4	202 bp	697 bp	153 bp	348 bp	788 bp
Mexico	5	5	3	4	4	133 bp	497 bp	331 bp	497 bp	1101 bp
Peru	4	2	4	4	4	169 bp	1287 bp	115 bp	841 bp	513 bp
Russia	5	5		7	4	162 bp	830 bp		623 bp	703 bp
South Africa	4	4	3	4	3	219 bp	1268 bp	566 bp	355 bp	578 bp

Table 5: Net Commodity Export to World

Reporter	Commodity	% Total Exports	% GDP
Australia	Energy	12%	2.0%
Australia	Metals	21%	3.6%
Brazil	Energy	-7%	-0.7%
Brazil	Metals	13%	1.4%
Canada	Energy	13%	3.6%
Canada	Metals	1%	0.2%
Chile	Energy	-17%	-5.3%
Chile	Metals	52%	16.5%
Colombia	Energy	43%	6.3%
Colombia	Metals	-1%	-0.2%
Indonesia	Energy	10%	2.8%
Indonesia	Metals	1%	0.2%
Malaysia	Energy	7%	6.0%
Malaysia	Metals	-3.0%	-2.6%
Mexico	Energy	6%	1.7%
Mexico	Metals	-2%	-0.4%
Peru	Energy	-6%	-1.1%
Peru	Metals	30%	6.5%
Russian Federation	Energy	61%	17.6%
Russian Federation	Metals	6%	1.7%
South Africa	Energy	-9%	-2.1%
South Africa	Metals	17%	3.8%

Each point represents the average of estimates calculated using annual data over the sample period 2000-2014. we use HS classifications: 26, 28, 72, 74 and 2502 for metals, and 27 for energy.

Source: COMTRADE.

Table 6: Robustness Tests: Baseline Model

		Period of Significant Effect			Trough Effect Period			Trough Effect		
Country	Model	Industrial Production	USD Exchange rate	Stock Market Index	Industrial Production	USD Exchange rate	Stock Market Index	Industrial Production	USD Exchange rate	Stock Market Index
Australia	Main Model	5 to 12	1 to 12	1 to 12	9	5	5	50 bp	261 bp	511 bp
Australia	RC1	5 to 12	3 to 12	1 to 12	9	6	6	37 bp	215 bp	427 bp
Australia	RC2	5 to 12	1 to 12	1 to 12	8	6	6	47 bp	250 bp	445 bp
Australia	RC3	5 to 12	1 to 12	1 to 12	9	5	5	49 bp	361 bp	539 bp
Australia	RC4		1 to 12	1 to 12		6	6		286 bp	622 bp
Australia	RC5	1 to 12		1 to 12	7		6	15 bp		176 bp
Australia	RC6		1 to 6	2 to 11		5	6		253 bp	445 bp
Brazil	Main Model	2 to 12	1 to 1	1 to 12	5	5	4	244 bp	157 bp	790 bp
Brazil	RC1	1 to 12	1 to 1	1 to 12	4	5	4	206 bp	166 bp	699 bp
Brazil	RC2	2 to 12	1 to 1	1 to 12	5	5	4	228 bp	162 bp	717 bp
Brazil	RC3	2 to 12	1 to 1	1 to 12	5	5	4	248 bp	193 bp	812 bp
Brazil	RC4	2 to 12	1 to 1	1 to 12	5	5	4	299 bp	181 bp	889 bp
Brazil	RC5	1 to 12	1 to 1	1 to 12	4	6	4	99 bp	87 bp	333 bp
Brazil	RC6	2 to 12	1 to 3	1 to 7	5	3	4	230 bp	271 bp	716 bp
Canada	Main Model		1 to 12	1 to 12		6	12		293 bp	484 bp
Canada	RC1	4 to 12	1 to 12	1 to 12	5	6	12	32 bp	271 bp	437 bp
Canada	RC2		1 to 12	1 to 12		6	12		290 bp	437 bp
Canada	RC3	4 to 12	1 to 12	1 to 12	5	6	12	45 bp	313 bp	527 bp
Canada	RC4		1 to 12	1 to 12		6	12		382 bp	641 bp
Canada	RC5	4 to 12	1 to 12	1 to 12	4	6	12	20 bp	125 bp	195 bp
Canada	RC6	4 to 12	1 to 12	1 to 12	5	7	12	48 bp	264 bp	424 bp
Chile	Main Model	1 to 1	1 to 5	1 to 1	1	3	4	78 bp	224 bp	171 bp
Chile	RC1	1 to 1	1 to 12	1 to 1	1	4	1	60 bp	189 bp	126 bp
Chile	RC2	1 to 1	1 to 6	1 to 1	1	3	4	68 bp	213 bp	139 bp
Chile	RC3	1 to 6	1 to 4	1 to 4	1	3	4	94 bp	201 bp	201 bp
Chile	RC4	1 to 1	1 to 4	1 to 1	1	3	4	102 bp	224 bp	197 bp
Chile	RC5	1 to 1	2 to 9	1 to 1	1	3	1	22 bp	97 bp	77 bp
Chile	RC6	1 to 1	1 to 5	1 to 1	1	3	4	78 bp	224 bp	171 bp
Colombia	Main Model	1 to 12		1 to 12	1		8	129 bp		704 bp
Colombia	RC1	1 to 12		1 to 12	1		8	106 bp		526 bp
Colombia	RC2	1 to 12		1 to 12	1		8	124 bp		611 bp
Colombia	RC3	1 to 12	5 to 12	1 to 12	1	12	8	139 bp	244 bp	790 bp
Colombia	RC4	1 to 12	5 to 12	1 to 12	1	7	8	151 bp	316 bp	1058 bp
Colombia	RC5	1 to 12		1 to 1	1		11	54 bp		171 bp
Colombia	RC6	1 to 12		1 to 12	1		8	129 bp		704 bp
Malaysia	Main Model	2 to 6	1 to 12	1 to 12	3	4	2	105 bp	148 bp	403 bp
Malaysia	RC1	2 to 12	1 to 12	1 to 12	5	4	2	99 bp	114 bp	346 bp
Malaysia	RC2	2 to 5	1 to 12	1 to 12	3	4	2	89 bp	133 bp	367 bp
Malaysia	RC3	2 to 12	1 to 12	1 to 12	3	4	2	108 bp	153 bp	406 bp
Malaysia	RC4	2 to 3	1 to 12	1 to 12	3	4	4	104 bp	166 bp	441 bp
Malaysia	RC5	3 to 12	1 to 4	1 to 12	5	4	1	62 bp	42 bp	160 bp
Malaysia	RC6	3 to 3	1 to 12	1 to 7	3	4	1	81 bp	131 bp	313 bp
Mexico	Main Model	5 to 12	1 to 12	1 to 12	5	10	7	41 bp	223 bp	443 bp
Mexico	RC1	5 to 12	1 to 12	1 to 12	5	7	7	32 bp	188 bp	378 bp
Mexico	RC2	5 to 12	1 to 12	1 to 12	5	10	7	32 bp	206 bp	392 bp
Mexico	RC3	4 to 12	1 to 12	1 to 12	5	10	7	56 bp	259 bp	511 bp
Mexico	RC4	5 to 12	1 to 12	1 to 12	5	7	7	41 bp	272 bp	517 bp
Mexico	RC5	4 to 12	3 to 12	1 to 12	5	7	7	13 bp	75 bp	139 bp
Mexico	RC6		1 to 12	1 to 12		7	7		273 bp	636 bp
Peru	Main Model	1 to 12	1 to 12	1 to 12	5	5	4	166 bp	130 bp	1022 bp
Peru	RC1	5 to 12	1 to 12	1 to 12	5	5	4	134 bp	105 bp	895 bp
Peru	RC2	1 to 12	1 to 12	1 to 12	5	5	4	147 bp	120 bp	944 bp
Peru	RC3	1 to 12	1 to 12	1 to 12	5	5	4	192 bp	140 bp	1077 bp
Peru	RC4	1 to 12	2 to 12	1 to 12	5	9	4	146 bp	135 bp	1095 bp
Peru	RC5	5 to 12	2 to 5	1 to 12	5	5	3	61 bp	32 bp	391 bp
Peru	RC6	1 to 12	1 to 12	1 to 12	5	5	4	166 bp	130 bp	1022 bp
Russia	Main Model	1 to 12	1 to 12	1 to 12	7	7	4	204 bp	434 bp	1574 bp
Russia	RC1	1 to 12	3 to 12	1 to 12	7	7	6	176 bp	415 bp	1365 bp
Russia	RC2	1 to 12	1 to 12	1 to 12	7	7	4	190 bp	417 bp	1426 bp
Russia	RC3	1 to 12	1 to 12	1 to 12	7	7	4	226 bp	442 bp	1684 bp
Russia	RC4	1 to 12	1 to 12	1 to 12	12	7	4	270 bp	562 bp	1879 bp
Russia	RC5	1 to 12	3 to 12	1 to 12	7	7	6	97 bp	244 bp	688 bp
Russia	RC6	1 to 12	1 to 12	1 to 12	7	7	4	204 bp	434 bp	1574 bp
S. Africa	Main Model	1 to 12	1 to 12	1 to 6	4	12	4	113 bp	329 bp	374 bp
S. Africa	RC1	1 to 12	2 to 12	1 to 7	4	6	4	88 bp	315 bp	370 bp
S. Africa	RC2	1 to 12	1 to 12	1 to 4	4	12	4	92 bp	306 bp	334 bp
S. Africa	RC3	1 to 12	1 to 12	1 to 10	4	6	4	122 bp	400 bp	401 bp
S. Africa	RC4	1 to 8	1 to 12	1 to 4	4	6	4	102 bp	514 bp	431 bp
S. Africa	RC5	1 to 12	2 to 12	1 to 4	4	12	4	44 bp	114 bp	157 bp
S. Africa	RC6	1 to 12	1 to 12	1 to 4	4	12	4	100 bp	277 bp	333 bp

Note: RC1- When deriving factors, we change the number of China variables in the DFM to 4; RC2- When deriving factors, we change the number of US variables to 10; RC3- The factors are derived from a DFM in which we allow China to affect US with a lag. It's a DFM with one lag of each factor. China factor now affects US variables with a lag; RC4- The factors are derived from a DFM with three factor lags; RC5- We take China IP growth rate instead of the China factor; and RC6- While performing FAVARs, we use AIC suggested number of lags of endogenous variables.

Table 7: Robustness Tests: Expanded FAVAR Model

		Period of Significant Effect					Trough Effect Period					Trough Effect				
Country	Model	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price
Australia	Main Model	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	12	2	5	5	5	56 bp	883 bp	299 bp	548 bp	715 bp
Australia	RC1	1 to 12	1 to 11	1 to 12	1 to 12	1 to 12	12	4	5	5	5	52 bp	794 bp	267 bp	452 bp	618 bp
Australia	RC2	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	12	4	5	5	5	53 bp	880 bp	285 bp	493 bp	651 bp
Australia	RC3	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	11	2	5	5	5	56 bp	915 bp	362 bp	565 bp	776 bp
Australia	RC4	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	12	2	5	5	5	45 bp	1011 bp	428 bp	634 bp	922 bp
Australia	RC5	1 to 12	1 to 4	1 to 12	1 to 12	1 to 12	12	4	5	4	5	26 bp	413 bp	110 bp	213 bp	275 bp
Australia	RC6	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	12	2	5	5	5	56 bp	883 bp	299 bp	548 bp	715 bp
Australia	RC7	1 to 12	1 to 12	1 to 12	1 to 12	1 to 12	6	2	5	5	5	56 bp	883 bp	296 bp	545 bp	710 bp
Brazil	Main Model	2 to 12	2 to 12		2 to 6	2 to 12	5	4		4	5	224 bp	1639 bp		609 bp	572 bp
Brazil	RC1	2 to 12	3 to 4		1 to 11	2 to 12	4	4		4	5	192 bp	1133 bp		556 bp	524 bp
Brazil	RC2	2 to 12	2 to 12		2 to 7	2 to 12	5	4		4	5	210 bp	1461 bp		562 bp	523 bp
Brazil	RC3	2 to 12	1 to 12		2 to 8	2 to 12	5	4		4	5	231 bp	1812 bp		655 bp	626 bp
Brazil	RC4	2 to 12	1 to 12		2 to 7	2 to 12	5	4		4	5	263 bp	2228 bp		666 bp	765 bp
Brazil	RC5	2 to 12	3 to 4		2 to 6	2 to 12	4	3		4	5	92 bp	530 bp		263 bp	241 bp
Brazil	RC6	2 to 12	2 to 12	1 to 1	2 to 6	2 to 6	5	4	1	6	5	215 bp	1615 bp	154 bp	575 bp	641 bp
Brazil	RC7	2 to 12	2 to 12		2 to 8	2 to 12	5	4		4	5	224 bp	1603 bp		618 bp	584 bp
Canada	Main Model			1 to 6	1 to 7	1 to 12			5	7	4			260 bp	422 bp	1101 bp
Canada	RC1			1 to 7	1 to 7	1 to 12			5	7	4			234 bp	374 bp	961 bp
Canada	RC2			1 to 6	1 to 7	1 to 12			5	7	4			250 bp	374 bp	1023 bp
Canada	RC3			1 to 7	1 to 11	1 to 12			5	7	4			270 bp	469 bp	1120 bp
Canada	RC4			1 to 7	1 to 9	1 to 12			5	7	4			327 bp	519 bp	1219 bp
Canada	RC5			1 to 5		1 to 12			5		3			108 bp		459 bp
Canada	RC6	4 to 5		1 to 12	1 to 12	1 to 12	5		7	11	4	47 bp		253 bp	366 bp	1092 bp
Canada	RC7			1 to 12	1 to 12	1 to 12			5	7	4			255 bp	411 bp	1106 bp
Chile	Main Model	1 to 1	1 to 6	2 to 3		1 to 12	1	3	3		6	77 bp	1025 bp	248 bp		783 bp
Chile	RC1	1 to 1	1 to 3	2 to 3	1 to 1	1 to 12	1	3	4	1	6	57 bp	826 bp	204 bp	113 bp	729 bp
Chile	RC2	1 to 1	1 to 3	2 to 3	1 to 1	1 to 12	1	3	3	4	6	67 bp	970 bp	226 bp	96 bp	729 bp
Chile	RC3	1 to 4	1 to 12	3 to 3		1 to 12	1	3	3		6	91 bp	1053 bp	220 bp		812 bp
Chile	RC4	1 to 1	1 to 12			1 to 12	1	3			6	98 bp	1400 bp			1058 bp
Chile	RC5		1 to 3	2 to 3	1 to 1	1 to 12		3	4	1	6		402 bp	105 bp	71 bp	349 bp
Chile	RC6	1 to 1	1 to 6	2 to 3		1 to 12	1	3	3		6	77 bp	1025 bp	248 bp		783 bp
Chile	RC7	1 to 1	1 to 10	2 to 3		1 to 12	1	3	3		6	77 bp	1025 bp	237 bp		772 bp
Colombia	Main Model	1 to 1			1 to 8	1 to 10	1			8	4	113 bp			623 bp	895 bp
Colombia	RC1	1 to 1			1 to 1	1 to 10	1			7	4	99 bp			418 bp	825 bp
Colombia	RC2	1 to 1			1 to 1	1 to 9	1			8	4	113 bp			517 bp	838 bp
Colombia	RC3	1 to 1			1 to 12	1 to 12	1			8	8	124 bp			716 bp	976 bp
Colombia	RC4	1 to 1			1 to 12	1 to 12	1			8	8	130 bp			957 bp	1113 bp
Colombia	RC5	1 to 1			1 to 1	1 to 6	1			7	3	50 bp			106 bp	391 bp
Colombia	RC6	1 to 1			1 to 8	1 to 10	1			8	4	113 bp			623 bp	895 bp
Colombia	RC7	1 to 5			1 to 12	1 to 12	1			8	4	113 bp			616 bp	888 bp

Note: RC1- When deriving factors, we change the number of China variables in the DFM to 4; RC2- When deriving factors, we change the number of US variables to 10; RC3- The factors are derived from a DFM in which we allow China to affect US with a lag. It's a DFM with one lag of each factor. China factor now affects US variables with a lag; RC4- The factors are derived from a DFM with three factor lags; RC5- We take China IP growth rate instead of the China factor; RC6- While performing FAVARs, we use AIC (SC for Australia and Mexico) suggested number of lags of endogenous variables; RC7- While performing FAVARs, we use different ordering of the variable- 'IP','CPI','SR interest rate', 'Commodity price','Exports','USD ex','Stock mkt index'.

Table 7: Robustness Tests: Expanded FAVAR Model (continued)

		Period of Significant Effect					Trough Effect Period					Trough Effect				
Country	Model	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price	Industrial Production	Exports to China	USD Exchange rate	Stock Market Index	Commodity Price
Malaysia	Main Model	2 to 3	1 to 12	1 to 4	1 to 5	1 to 12	3	3	4	2	4	96 bp	1049 bp	131 bp	372 bp	1129 bp
Malaysia	RC1	1 to 5	1 to 12	1 to 2	1 to 5	1 to 12	3	3	4	2	4	100 bp	832 bp	99 bp	319 bp	1012 bp
Malaysia	RC2	3 to 3	1 to 11	1 to 2	1 to 4	1 to 12	3	3	4	2	4	81 bp	1001 bp	113 bp	336 bp	1068 bp
Malaysia	RC3	2 to 3	1 to 12	1 to 4	1 to 6	1 to 12	3	3	4	2	4	90 bp	1061 bp	128 bp	364 bp	1140 bp
Malaysia	RC4		1 to 10	1 to 2	1 to 5	1 to 12		5	4	4	4		1299 bp	144 bp	432 bp	1247 bp
Malaysia	RC5	1 to 7	1 to 12	1 to 1	1 to 5	1 to 12	3	3	4	2	3	60 bp	452 bp	35 bp	143 bp	505 bp
Malaysia	RC6	2 to 3	1 to 12	1 to 4	1 to 5	1 to 12	3	3	4	2	4	96 bp	1049 bp	131 bp	372 bp	1129 bp
Malaysia	RC7	2 to 3	1 to 12	1 to 4	1 to 12	1 to 12	3	3	4	2	4	96 bp	1058 bp	128 bp	370 bp	1130 bp
Mexico	Main Model			1 to 3	1 to 12	1 to 12			6	7	4			204 bp	493 bp	1029 bp
Mexico	RC1				1 to 10	1 to 12				7	4				395 bp	927 bp
Mexico	RC2				1 to 10	1 to 12				7	4				433 bp	956 bp
Mexico	RC3	5 to 5		1 to 6	1 to 12	1 to 12	5		6	7	4	51 bp		241 bp	563 bp	1068 bp
Mexico	RC4				1 to 9	1 to 12				7	4				577 bp	1116 bp
Mexico	RC5				1 to 1	1 to 12				7	3				137 bp	441 bp
Mexico	RC6			3 to 12	1 to 12	1 to 12			5	5	4			206 bp	524 bp	1238 bp
Mexico	RC7	5 to 12		1 to 12	1 to 12	1 to 12	5		6	7	4	37 bp		201 bp	488 bp	1024 bp
Peru	Main Model	1 to 12	1 to 3		1 to 12	1 to 12	5	1		4	6	154 bp	871 bp		899 bp	803 bp
Peru	RC1	5 to 12	1 to 1		1 to 12	1 to 12	5	3		4	6	122 bp	575 bp		753 bp	694 bp
Peru	RC2	1 to 12	1 to 3		1 to 12	1 to 12	5	1		4	6	135 bp	807 bp		809 bp	703 bp
Peru	RC3	1 to 12	1 to 3		1 to 12	1 to 12	5	1		4	6	180 bp	1006 bp		951 bp	824 bp
Peru	RC4		1 to 3		1 to 12	1 to 12		1		4	11		946 bp		965 bp	1122 bp
Peru	RC5	5 to 5			1 to 6	1 to 12	5			3	5	54 bp			304 bp	295 bp
Peru	RC6	1 to 12	1 to 1		1 to 12	1 to 12	5	1		4	6	152 bp	861 bp		885 bp	825 bp
Peru	RC7	1 to 12	1 to 3		1 to 12	1 to 12	5	1		4	6	151 bp	866 bp		889 bp	786 bp
Russia	Main Model	1 to 12	3 to 12	4 to 6	1 to 12	1 to 12	7	4	6	4	4	184 bp	1269 bp	354 bp	1486 bp	1174 bp
Russia	RC1	1 to 12	3 to 12	5 to 7	1 to 12	1 to 12	7	4	6	6	4	154 bp	997 bp	315 bp	1237 bp	1038 bp
Russia	RC2	1 to 12	3 to 12	4 to 5	1 to 12	1 to 12	7	4	6	4	4	168 bp	1232 bp	330 bp	1331 bp	1102 bp
Russia	RC3	1 to 12	3 to 12	4 to 10	1 to 12	1 to 12	7	4	5	4	4	205 bp	1316 bp	356 bp	1598 bp	1196 bp
Russia	RC4	1 to 12	3 to 12	4 to 6	1 to 12	1 to 12	11	4	6	4	4	237 bp	1495 bp	437 bp	1766 bp	1320 bp
Russia	RC5	2 to 12	3 to 12	5 to 7	1 to 12	1 to 12	7	4	6	4	4	82 bp	512 bp	187 bp	600 bp	529 bp
Russia	RC6	1 to 12	3 to 12		1 to 12	1 to 12	5	4		4	4	177 bp	1267 bp		1446 bp	1086 bp
Russia	RC7	1 to 12	3 to 12	4 to 12	1 to 12	1 to 12	7	4	6	4	4	185 bp	1256 bp	355 bp	1489 bp	1177 bp
S. Africa	Main Model	1 to 10	2 to 3	2 to 3	1 to 4	2 to 12	4	3	6	4	5	96 bp	892 bp	297 bp	233 bp	667 bp
S. Africa	RC1	1 to 4	2 to 3		1 to 4	2 to 12	4	3		4	5	76 bp	667 bp		227 bp	567 bp
S. Africa	RC2	1 to 4	2 to 3		1 to 4	2 to 12	4	2		4	5	77 bp	854 bp		207 bp	610 bp
S. Africa	RC3	1 to 12	2 to 3	2 to 12	1 to 4	2 to 12	4	2	6	4	6	105 bp	917 bp	375 bp	260 bp	731 bp
S. Africa	RC4		2 to 3	2 to 12	1 to 4	2 to 12		3	6	4	6		1078 bp	492 bp	259 bp	920 bp
S. Africa	RC5	1 to 4	2 to 2		1 to 1	2 to 11	4	3		4	5	38 bp	290 bp		92 bp	237 bp
S. Africa	RC6	1 to 4	3 to 3		1 to 4	2 to 12	4	3		4	6	89 bp	768 bp		215 bp	655 bp
S. Africa	RC7	1 to 12	2 to 3	2 to 3	1 to 4	2 to 12	4	3	12	4	5	96 bp	904 bp	294 bp	234 bp	672 bp

Note: RC1- When deriving factors, we change the number of China variables in the DFM to 4; RC2- When deriving factors, we change the number of US variables to 10; RC3- The factors are derived from a DFM in which we allow China to affect US with a lag. It's a DFM with one lag of each factor. China factor now affects US variables with a lag; RC4- The factors are derived from a DFM with three factor lags; RC5- We take China IP growth rate instead of the China factor; RC6- While performing FAVARs, we use AIC (SC for Australia and Mexico) suggested number of lags of endogenous variables; RC7- While performing FAVARs, we use different ordering of the variable- 'IP','CPI','SR interest rate', 'Commodity price','Exports','USD ex','Stock mkt index'.

Table 8: Rank by Output effect of China shock in 5-variable FAVAR

Model	Brazil	Russia	Peru	Australia	Canada	Mexico	Chile	Malaysia	Colombia	S. Africa
Main Model	1	2	3	8	10	9	7	6	4	5
RC1	1	2	3	8	9	10	7	5	4	6
RC2	1	2	3	8	10	9	7	6	4	5
RC3	1	2	3	9	10	8	7	6	4	5
RC4	1	2	4	9	10	8	6	5	3	7
RC5	1	2	4	9	8	10	7	3	5	6
RC6	1	2	3	9	8	10	7	6	4	5