The Impact of China's Slowdown on the Asia Pacific Region

An Application of the GVAR Model

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Abstract

An export-oriented development strategy fostered the Asia Pacific region's economic success, making it the fastest growing region in the world. In recent years, despite waning demand from the crisis-hit Western economies, the accelerating demand from China boosted intraregional trade in Asia. Although China's Asian trading partners benefit from increasing exports to China, this stronger linkage with China has made them more vulnerable to the risk of a Chinese slowdown. This paper examines the impact of a negative Chinese gross domestic product (GDP) shock on Asian economies by employing the Global Vector Autoregressive (GVAR) model, using the dataset through the third quarter of 2014 for 33 countries. The analysis finds that a negative Chinese GDP shock impacts commodity exporters,

such as Indonesia, to the greatest extent, reflecting both demand and terms of trade shocks. Export-dependent countries in the East Asian production cycle, such as Japan, Malaysia, Singapore and Thailand, are also severely affected. The analysis also finds that a negative shock to China's real GDP would not only have an adverse effect on the price of crude oil, as some previous studies have also shown, but also on the prices of metals and agricultural products. The study also investigates the impact of a potential negative shock to the real GDP of the United States on Asian countries, and determines that although the U.S. economy has a larger influence on Asian economies than China's economy, the Asian countries are more exposed to China than ever through increased economic ties.

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The Impact of China's Slowdown on the Asia Pacific Region: An Application of the GVAR Model*

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1 Introduction

Global economic integration has expanded dramatically over the past two decades. Global trade surged to \$37 trillion in 2014 from \$6 trillion in 1990. Led by China, Asia Pacific countries' trade levels rose 18 times over this period, which is faster than any other regional country groups.¹ The export-oriented development strategy brought the Asia Pacific region economic success through rapid growth, making it the fastest growing region and the world's growth engine. On the other hand, increased integration and dependence on exports intensified the region's vulnerability to external shocks.

Since 2008, due to the anemic growth in the United States and the recession in the Eurozone, the advanced economies' demand for Asia Pacific exports has been waning. Nevertheless, thanks to surging Chinese demand, the rest of the Asia Pacific countries' ("Asia" henceforth) exports remained as a positive outlier. The Asian exports to China doubled over the last five years and China became the largest market for Asia after surpassing Japan in 2005 and the US in 2007. As China became the central point of the Asian supply chain, its demand has been supporting the region's production of goods ranging from raw materials to electronic components.² Despite the recent acceleration in the US economy, the advanced economies' overall growth expectations remain subdued; therefore, China's continuing role supporting the Asian economies remains critical. However, China's economy is slowing down from the rapid growth rates exceeding 10 percent over the past several decades. The real GDP growth in 2014 was 7.4 percent, which was the weakest in 24 years. Further slowdown is expected going forward, and some projections show growth rates dropping to about 6 percent by the end of the decade.

Against this background, we aim to examine and quantify the impact of a negative

¹The Asia Pacific countries in this paper are defined by the ten largest countries in the Asia Pacific Region in terms of GDP, i.e. ASEAN-4 (Indonesia, Malaysia, the Philippines and Thailand), Australia, China, India, Japan, the Republic of Korea and New Zealand.

²China's "export powerhouse" role undeniably contributed to other regions' growth particularly those of the commodity exporters in Latin America and Africa; however, this paper will only focus on China's linkages to Asia.

Chinese GDP shock on Asian economies by employing the Global Vector Autoregression (GVAR) model developed by Pesaran, Schuermann and Weiner (2004), and Dees, di Mauro, Pesaran, and Smith (2007). Through GVAR, we examine how and to what extent the Chinese economic growth affects Asian countries. The transmission mechanism of this slowdown may be diversified: in this paper we examine the shocks to the real economy based on trade linkages. For simplicity, the original GVAR model assumes a fixed trade weight for the sample period. However, considering the recent rapid expansion of Chinese trade volume, both in exports and imports, we find that the “fixed weight” assumption is not optimal. Thus, following Cesa-Bianchi, Pesaran, Rebucci, and Xu (2011; henceforth CPRX), we construct a model with time-varying trade relations. After estimating the GVAR model, we calculate a set of generalized impulse response functions (henceforth GIRFs) for four different timings³ with different trade weights, and investigate the changes of the shock propagation mechanism from China to the Asian countries.⁴

To the best of our knowledge, Han and Ng (2011) is the first study that focuses its analysis on Asia’s economies using the GVAR methodology; however, its focus was on evaluating macroeconomic forecasts for the original ASEAN economies. Matsubayashi (2013) examined the impact of the financial crisis in the US and Eurozone on the East Asian countries using GVAR with a time-varying weight matrix. In light of structural change in world trade around 1995, Matsubayashi has also estimated the GVAR model using a sample up to 1994Q4, and compared its impulse response functions (henceforth IRFs) with the ones obtained from the entire sample period. Matsubayashi reported that the impact of the US and Eurozone on Asian countries, especially China, is becoming larger since the last half of 1990s, reflecting the tighter trade linkages between China and the US and Eurozone.

Several recent studies examined the impact of the Chinese slowdown employing various

³As we discuss below, China’s membership of the World Trade Organization in 2001 dramatically altered the outlook of global trade. Thus, we have investigated the effect of China at years 1985, 1995, 2005, and 2013. Two of them are before joining, and two others are after joining the WTO.

⁴The focus of CPRX was to investigate the effect of the Chinese economy on the Latin American countries.

techniques. The IMF’s China Country Report (2011)⁵ analyzed the spillover effects of domestic policies in China. Based on the work by Chen, Gray, N’Diaye, Oura, and Tamirisa (2010),⁶ the report assessed how the worsening credit quality of the Chinese corporates and banks negatively affects the rest of the world by using the GVAR. Ahuja and Nabar (2012a, b) is another example. They have investigated the impact of two different sources of China’s slowdown: one is the real estate investment slowdown, and the other is a slowdown in investment spending (as a component of GDP). One last example is a paper by Duval et al. (2014). They have examined the relationship between trade integration and business cycle synchronization, and reported how China’s growth shocks are associated with the real GDP growth of other countries.

These papers are different from ours in several respects. First, the sample period is shorter than ours. Chen et al. (2010) uses monthly data for the period January 1996 to December 2008, Duval et al. (2014) uses 1995Q1-2012Q4, and Ahuja and Nabar (2012a,b) January 2000 to September 2011. Our dataset ranges from 1979Q1 to 2014Q3, thus covering the period when the size of Chinese economy and its regional and global influence expanded over more than three decades. The second difference concerns the measurement of country linkages. Duval et al. (2014), for instance has reported the importance of using value-added trade data for measuring trade integration. On the other hand, Chen et al. (2010) used financial weights and trade weights to construct foreign variables. However, due to limited data, they used fixed weights for both financial and trade linkages. Reflecting the lack of historical time series data, as reported by previous researchers, and following the tradition of GVAR literature by Pesaran and others, we have decided to use the gross trade flow data. Thirdly, except for Chen et al (2010), the models are different: Ahuja and Nabar (2012a,b) used FAVAR, and Duval et al. (2014) used a reduced-form panel regression model. We used the GVAR specification because it imposes an intuitive structure on cross-country interlinkages (Chudik and Pesaran, 2014), and also allows us to measure the responses of

⁵URL is <http://www.imf.org/external/pubs/ft/scr/2011/cr11193.pdf>

⁶URL is <https://www.imf.org/external/pubs/ft/wp/2010/wp10124.pdf>

major macroeconomic variables.

Our results confirm that the impact of a negative shock to Chinese real GDP on the Asian countries has significantly increased under the recent trade structures of 2005 and 2013 compared to the earlier trade structures of 1985 and 1995. This confirms the common understanding of Asia’s increased dependency on China. The GIRFs are significantly negative with the exception of the Philippines and New Zealand. All remaining Asian countries are negatively impacted by a real GDP shock to the Chinese economy at the 68% interval. China’s slowdown also curbs its demand for commodities, and we investigated whether this translates into commodity price drops. Our GIRFs show that a negative shock to the real GDP of China not only reduces crude oil prices, as some previous studies have shown, but also metals and agricultural prices. We also ran our model to test the impact of a potential US real GDP shock, and confirms that although the US has a stronger influence on Asian economies than China, these countries are more exposed to China than ever through increased economic ties.

The rest of the paper is organized as follows. In Section 2, we analyze the historical transition of the Chinese trade volume using trade data. In Section 3, we explain the standard GVAR model following past studies, and introduce several modifications, such as the time-varying trade weights, increasing the number of commodities, and inclusion of the “shift in intercepts” dummy variables to control the outliers. In Section 4, we estimate the model. In Section 5, we calculate the GIRFs, and investigate the effect of a Chinese economic shock on the Asian countries by comparing the shapes of the GIRFs with various settings. Section 6 summarizes our conclusions.

2 The transition of China’s trade share

China’s membership of the World Trade Organization in 2001 dramatically altered the outlook for global trade and became a turning point for the country’s economic development.

Figure 1: Trade Links between China, Asia, and the World

Source: IMF Direction of Trade Statistics; Authors' calculation.

In the left panel of Figure 1, we see how the share of exports of Asian countries to China evolved over the past several decades. We observe a significant jump since 2001: particularly, exports of Australia, Japan and the Republic of Korea to China have expanded more than three-fold. Likewise, the Asian countries' imports from China have been rising considerably in recent years (see the right panel of Figure 1). In particular, Australia, Japan, the Republic of Korea, Malaysia and the Philippines saw the largest rise in their imports from China.

China's share of world trade rose from about 4 percent in 2000 to around 11 percent last year. Figure 2 shows the evolution of trade shares of each country in 1985, 1995, 2005, and 2013. While the United States, Japan and Eurozone countries have seen decline in their share of trade in the global economy, China's trade share rose in recent years. China is now the largest trading nation in the world after surpassing the US, and is the largest trading partner for 35 countries across the globe. In our sample of nine Asian countries, China is the largest trading partner of seven countries (Australia, India, Japan, the Republic of Korea, Malaysia, New Zealand and Thailand), the second largest trading partner of Indonesia and third largest of the Philippines.

In the next section, we explain the GVAR methodology. As we just reviewed above, China's trade linkages drastically changed shortly after China joined the WTO in December 2001. Thus, we expect that the magnitudes of shock propagations from China to the

Figure 2: Trade weights of 1985, 1995, 2005, and 2013 for 12 sample countries

Source: IMF Direction of Trade Statistics; Authors' calculation. Please refer to Table A1 in the Appendix for a glossary of acronyms.

global economy before and after the year 2001 to be quite different. Given these changes, we introduce several modifications in order to analyze China’s economic impact on Asian countries.

3 Analytical tool: The GVAR model

Our main goal is to measure the impact of China’s economic slowdown and in order to do so, we assume a scenario where China’s real economic growth declines by one percent.

In order to quantify this change we use a novel time-series technique: the GVAR model, which was originated by Pesaran, Schuermann, and Weiner (2004), Dees, di Mauro, Pesaran, and Smith (2007), and Dees, Holly, Pesaran, and Smith (2007). Due to its modeling flexibility, the GVAR model was applied to various fields such as macroeconomics (Dees, di Mauro, Pesaran, and Smith, 2007), industrial sectors (Hiebert and Vansteenkiste, 2010), bond markets (Favero, 2013), real estate markets (Vansteenkiste, 2007), fiscal imbalance on borrowing costs (Caporale, G., M., and A. Girardi, 2013), and US credit supply shocks (Eickmeier, S., and T. Ng, 2015). It was also applied to examine the financial crisis (Chudik, A., and M. Fratzscher, 2011), and the interactions between banking sector risk, sovereign risk, corporate sector risk, and real economic activity (Gray,D., M.Gross, J.Paredes, and M. Sydow, 2013).

In the following section, we first review the structure of the standard GVAR model. Next, we explain several modifications, which are necessary to achieve our objectives.

3.1 Structure of the standard GVAR model

The standard VAR of country i is a stand-alone model in the sense that it specifies the inter-temporal as well as inter-variable relation among a set of country i ’s macroeconomic variables, $\mathbf{x}_{it}$. The VAR(p) of country i , which includes p -th order lag of $\mathbf{x}_{it}$, is represented as follows:

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \sum_{k=1}^p \Phi_{ik}\mathbf{x}_{i,t-k} + \mathbf{u}_{it}$$

where $\mathbf{a}$ and Φ and the coefficient vectors. A vector of country-specific shocks, $\mathbf{u}_{it}$, is assumed to be distributed serially uncorrelated with zero mean and a nonsingular covariance matrix, i.e. $\mathbf{u}_{it} \sim i.i.d.(0, \Sigma_{ii})$. With this specification, all variables of $\mathbf{x}_{it}$ are assumed to be endogenous in general, thus interactively determined within its economy.

There are variables that are determined outside the country of interest. The price of crude oil, which largely reflects the demand and supply conditions in the world market, is one such example. For a small-open economy, it is more likely that the oil price is exogenously determined. Thus we expand the VAR model and add such global variables, $\mathbf{d}_{it}$, as follows:

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \sum_{k=1}^p \Phi_{ik} \mathbf{x}_{i,t-k} + \sum_{\ell=0}^r \Upsilon_{i\ell} \mathbf{d}_{i,t-\ell} + \mathbf{u}_{it}$$

A VAR model with exogenous variables is called “VARX”.⁷

The GVAR model consists of a set of county-by-country VAR models that includes a set of “country-specific foreign variables” $\mathbf{x}_{it}^*$, which is constructed by taking the weighted average across all the countries j of the corresponding variable as follows:

$$\mathbf{x}_{it}^* = \sum_{j=1}^N \omega_{ij} \cdot \mathbf{x}_{jt} \quad (1)$$

where the weights satisfy $\omega_{ii} = 0$ and $\sum_{j=1}^N \omega_{ij} = 1$ for $i = 1, \dots, N$. Since this weight represents the closeness of the economic activities between the countries, the trade share, which is constructed by using the bi-directional trade flow data, is often used.

The VARX^{*}(p, q, r) of country i , which includes p -th order lag of $\mathbf{x}_{it}$, q -th order lag of $\mathbf{x}_{it}^*$ and r -th order lag of $\mathbf{d}_{it}$, is represented as follows:

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \sum_{k=1}^p \Phi_{ik} \mathbf{x}_{i,t-k} + \sum_{\ell=0}^q \Lambda_{i\ell} \mathbf{x}_{i,t-\ell}^* + \sum_{\ell=0}^r \Upsilon_{i\ell} \mathbf{d}_{i,t-\ell} + \mathbf{u}_{it} \quad (2)$$

⁷The treatment of the oil price may vary across countries. For a large-open economy, such as the US, it is plausible to assume that the oil price is determined domestically. Therefore it should be included in $\mathbf{x}_{it}$.

where $\mathbf{a}$, Φ , Λ , and Υ are the coefficient vectors. Since this specification includes the foreign variables (“star” variables) and the global variables, both of which are assumed to be weakly exogenous, the model is called VARX*.

When we estimate the country-specific VARX*, $\mathbf{x}_{it}^*$ are constructed directly from the data. However, for dynamic analysis such as calculating the impulse response functions, the value of $\mathbf{x}_{it}^*$ is calculated internally from the forecasted values of $\{\mathbf{x}_{jt}^*\}$ for $i \neq j$, which are obtained by solving the system of Equations (1) and (2). This is why the GVAR model can describe the interactions of variables not only within a country but also between countries.

3.2 Data and a related specification issue

In this paper, following CPRX, we have estimated 26 country-specific VARX* models.⁸ Based on the dataset obtained from Centre for Financial Analysis & Policy, Judge Business School, University of Cambridge,⁹ which covers the periods from 1979Q1 to 2011Q2, we have extended the dataset up to 2014Q3 in order to investigate the up-to-date impact of the Chinese economy on the world. The GDP of these 26 countries adds up to approximately 90% of the world GDP; therefore we claim that the model covers the world economy.

The standard elements of three variables in Equation (2) in the related literature are as follows. The domestic variables, $\mathbf{x}_{it}$, include the real GDP y_{it} , the inflation rate π_{it} , the real exchange rate $e_{it} - p_{it}$, the real equity prices q_{it} , the short-term interest rate ρ_{it}^S , and the long-term interest rate ρ_{it}^L . Since q_{it} , ρ_{it}^S , and ρ_{it}^L are missing for some countries, they are included when available.¹⁰ The foreign variables, $\mathbf{x}_{it}^*$, are constructed as defined by Equation (1). As for the global variables, $\mathbf{d}_{it}$, the log of oil price index p_t^O is included in order to

⁸Since one of the economies is the Eurozone, which consists of eight countries, i.e. Germany, France, Italy, Spain, Netherlands, Belgium, Austria, and Finland, the total number of countries in our data is 33.

⁹We have downloaded GVAR Data 1979Q1–2011Q2 (2011 Vintage) from “The GVAR Toolbox” website at Centre for Financial Analysis & Policy, Judge Business School, University of Cambridge. URL is <http://www.cfap.jbs.cam.ac.uk/research/gvartoolbox/download.html>. The most updated dataset currently available is 2013 Vintage at “Global VAR Modelling” website created by Dr. L. Vanessa Smith. URL is <https://sites.google.com/site/gvarmodelling/>.

¹⁰Specifically, the definitions of the variables are as follows: $p_{it} = \ln(\text{CPI}_{it})$, $q_{it} = \ln(\text{EQ}_{it}/\text{CPI}_{it})$,

Table 1: Set of variables used for country-specific VARX* models

	non-US model ($i \neq \text{US}$)			US model ($i = \text{US}$)		
	domestic	foreign	global	domestic	foreign	global
	$\mathbf{x}_{it}$	$\mathbf{x}_{it}^*$	$\mathbf{d}_{it}$	$\mathbf{x}_{it}$	$\mathbf{x}_{it}^*$	$\mathbf{d}_{it}$
real GDP	y_{it}	y_{it}^*		y_{it}		
inflation rate	π_{it}	π_{it}^*		π_{it}		
real equity price	q_{it}	q_{it}^*		q_{it}		
short-term interest rate	ρ_{it}^S	ρ_{it}^{S*}		ρ_{it}^S		
long-term interest rate	ρ_{it}^L	ρ_{it}^{L*}		ρ_{it}^L		
real exchange rate	$e_{it} - p_{it}$				$e_{it}^* - p_{it}^*$	
oil price			p_t^O	p_t^O		
metal price			p_t^M	p_t^M		
agricultural price			p_t^A	p_t^A		

capture the influences from the international commodity market.¹¹

The dataset contains various types of countries. Twenty-six economies are divided into two types; the large-open economy and the small-open economies. The US is classified as the only large open economy. For this type, it is assumed that the foreign financial markets do not affect its economy. Also, the international commodity prices are included in the model representing its economy. See Dees, di Mauro, Pesaran, and Smith (2007) and CPRX(2011) for similar treatment. Although the instantaneous commodity prices are only included in the US model, other countries, such as China, can influence it through trade linkages but with a time lag. Thus in the US model, three commodity prices, i.e. p_t^O , p_t^M and p_t^A , are included in $\mathbf{x}_{\text{US},t}$, and foreign financial variables, i.e. $q_{\text{US},t}^*$, $\rho_{\text{US},t}^{S*}$ and $\rho_{\text{US},t}^{L*}$, are excluded from

$e_{it} = \ln(E_{it})$, $\rho_{it}^S = 0.25 * \ln(1 + R_{it}^S/100)$, and $\rho_{it}^L = 0.25 * \ln(1 + R_{it}^L/100)$, where

- GDP_{it} = nominal GDP, in local currency
- CPI_{it} = consumer price index; base year is 2000
- EQ_{it} = nominal equity price index
- E_{it} = exchange rate of country i in terms of US dollars
- R_{it}^S = short-term interest rate per annum
- R_{it}^L = long-term interest rate per annum

y_{it} is constructed as follows: 1) calculate the real GDP by $\text{GDP}_{it}/\text{CPI}_{it}$; 2) from the 2006-2008 average of PPP-GDP, calculate the relative size of real GDPs for 2006-2008; 3) rescale the real GDP of each country, with US GDP as a baseline; 4) take the logarithm.

¹¹It is possible to include the global variables for some countries, but exclude them for the other countries. Thus we added country index “ i ” to its subscript.

$\mathbf{x}_{\text{US},t}^*$. This means that, for the US, the global variable $\mathbf{d}_{\text{US},t}$ is empty.

For the rest of the sample economies, it is assumed that both the international commodity markets and the foreign financial markets influence their economies. Thus for economy i , three commodity prices are included in $\mathbf{d}_{it}$, and three foreign financial variables are included in $\mathbf{x}_{it}^*$.

Lastly, regarding the real exchange rate, we include $e_{it} - p_{it}$ in $\mathbf{x}_{it}$ for the remaining economies. However, conversely, it implies that the value of US currency is determined outside the US economy, and thus $e_{\text{US},t}^* - p_{\text{US},t}^*$ is treated as a part of a “US-specific foreign” variable.

3.3 Several modifications

In order to appropriately measure the effect of China’s emergence in the global economy, we introduce several modifications to the standard GVAR model. They are:

1. making the weight matrix ω_{ij} time-varying
2. adding the metal price index p_t^M and the agricultural price index p_t^A to $\mathbf{d}_{it}$
3. detecting the structural breaks

The importance of these aspects will be discussed below.

3.3.1 Making the weight matrix ω_{ij} time-varying

Previously, a set of “country-specific foreign variables” $\mathbf{x}_{it}^*$ was defined as Equation (1), which is constructed by using a constant weight matrix, ω_{ij} . Now, it is modified as:

$$\mathbf{x}_{it}^* = \sum_{j=1}^N \omega_{ij}(t) \cdot \mathbf{x}_{jt} \quad (3)$$

so that the evolving between-countries closeness is measured by a sequence of time-varying weights, which satisfies $\omega_{ii}(t) = 0$ and $\sum_{j=1}^N \omega_{ij}(t) = 1$ for $i = 1, \dots, N$.

To our best knowledge, the first published application of a time-varying weight matrix was used by CPRX (2011), who investigated the impact of China’s economic growth on the Latin American countries.

Since this weight represents the closeness of the economic activities between the countries, the ideal weights should properly reflect this magnitude. In the literature of GVAR, either one of two candidates is often used. One is the trade weight, which is constructed by using the bi-directional trade flow data. The other is the financial weight, which represents the flow of funds between the countries.

As we have examined in Section 2, China’s trade linkages with the rest of the world have drastically increased after China joined the WTO in 2001. Although the financial linkages are deepening, the trade linkages continue to define China’s economic impact. Besides, the quality of data used for constructing the trade weight is more reliable than that of financial weight, and these data are available from the 1980s.¹² Thus we construct $\omega_{ij}(t)$ by using the three-year averages of bi-directional trade flow data, obtained from the IMF’s Direction of Trade Statistics.

3.3.2 Adding two commodity price indices

In the literature, the standard GVAR models are estimated with only one global variable, i.e. the crude oil price, which is the representative of commodity “energy”. According to Table 2, which reports the shares used for calculating the World Bank’s Commodity Price Index, the share of crude oil in the energy index is 84.6%. The importance and the influence of crude oil price fluctuations on the macroeconomic variables of countries, such as the US, are reported by numerous researchers. Just to name a few, Hamilton (1983, 1996, 2003), Hooker (1996), and Cunado and de Gracia (2005).

Besides “energy”, the World Bank publishes two more commodity indices, i.e. “non-energy commodities” and “precious metals” (See Table 2); and the “non-energy commodi-

¹²For more discussion, see CPRX (2011).

Table 2: Shares used in the World Bank’s Commodity Price Index, in percentage

Commodity	Share	Commodity	Share
<i>Energy</i>		<i>Non-energy Commodities</i>	
Coal	4.7	Agriculture	64.9
Crude Oil	84.6	Food	40.0
Natural Gas	10.8	Others	24.8
		Metals and Minerals	31.6
		Aluminum	8.4
<i>Precious Metals</i>		Copper	12.1
Gold	77.8	Iron Ore	6.0
Silver	18.9	Others	5.1
Platinum	3.3	Fertilizers	3.6
Source: World Bank, Development Prospects Group. Based on 2002-04 developing countries’ export values. November 24, 2008.			

ties” group is further divided into “agriculture”, “metals and minerals”, and “fertilizers”. The sum of “agriculture” and “metals and minerals” adds up to 96.5%. Since China is a major importer of metals and agricultural products, it is worth investigating the importance of including these indices in $\mathbf{d}_{it}$, which allows us to model the multiple channels of impact propagation through the international commodity markets.

Table 3 summarizes the covariance analysis of three commodity prices (in log-differences). The price of oil is the most volatile and the price of agricultural products is the least volatile. In terms of the instantaneous correlation coefficients, $\text{Corr}(\Delta p_t^M, \Delta p_t^A) = 0.5506$ is the highest, $\text{Corr}(\Delta p_t^M, \Delta p_t^O) = 0.4506$ is the second highest, and $\text{Corr}(\Delta p_t^A, \Delta p_t^O) = 0.3171$ is the lowest. It is often reported that both metals and agricultural products require a fair amount of energy as an intermediate input. There is higher correlation between metals and oil, but this is not supported by the correlation between agriculture and oil.

In order to further investigate the inter-variable relationship, a plain three-variate VAR model is estimated for $\Delta p_t^O, \Delta p_t^A, \Delta p_t^M$, and the causal relation is examined by the Granger causality test. The optimal lag length of VAR, three, is selected by AIC. Table 4 reports the results. The second column is the equation for “oil”, where the exclusion hypothesis of “metal” is rejected at a 10% significance level. For the “agri” equation, neither “oil” nor “metal” is a significant causal variable. Lastly, for the “metal” price, there is strong Granger

Table 3: Covariance analysis of three commodity price indices

Covariance / <i>Correlation</i>	Oil Δp_t^O	Agri Δp_t^A	Metal Δp_t^M
Oil	0.0199 <i>1.0000</i>		
Agri	0.0022 <i>0.3171</i>	0.0025 <i>1.0000</i>	
Metal	0.0061 <i>0.4506</i>	0.0026 <i>0.5506</i>	0.0091 <i>1.0000</i>

Note: $p_t^k = \ln(\text{price index of commodity } k)$ for $k = O, A, M$

Table 4: VAR Granger causality/Block exogeneity Wald tests

	Dependent variable		
	Oil Δp_t^O	Agri Δp_t^A	Metal Δp_t^M
Oil		1.755	3.015
Agri	4.881		20.808***
Metal	7.479*	4.122	
All	15.155**	5.148	23.228***

Note: Three commodity prices are log-differenced. VAR(3) is used.
 ***, **, *, represent 1 percent, 5 percent, and 10 percent significance levels, respectively.

causality from the “agri” price. These results again contradict the view that “oil” is the foremost intermediate input, so that a hike of the oil price increases both agricultural and metal prices.

Given this preliminary analysis, we are now confident that the inclusion of agricultural and metal prices provides additional information, which is not revealed by inclusion of only oil prices.

3.3.3 Detecting the structural breaks with a difference-stationary VAR

As we formally report below, all the variables in our VARX* are the I(1) processes. Thus if they are co-integrated, the VARX* model can be transformed into a vector error correction model with exogenous variables. The previous papers in this field have mostly adopted this specification, which makes us impose any long-run relations that might exist in the economy,

and increases the efficiency of parameter estimation.

However, as our sample covers the period between 1979Q1 and 2014Q3, it surely includes influential events such as the Asian Financial Crisis in 1997, the Lehman Shock in 2008, etc., which are likely to generate the structural breaks. The difficulty of detecting the structural break with the co-integrating VAR is reported by Hendry (2000).

A strand of research combines the Bayesian methods and the vector error correction models (henceforth VECM). Jockmann and Koop (2011), for instance, have incorporated the Markov switching into the VECM, which allows both the cointegrating vectors and the number of cointegrating relationships to change when the regime changes. Even though it is a fascinating approach, the computational burden outweighs the benefits when it is applied to the GVAR.¹³ Besides, our aim is not forecasting but the historical evaluation of China's impact. Therefore, we treat the issue of structural breaks in a simpler manner.

First, the following “difference-stationary” VAR specification is used from now on:

$$\Delta \mathbf{x}_{it} = \mathbf{a}_{i1} + \sum_{k=1}^{p-1} \tilde{\Phi}_{ik} \Delta \mathbf{x}_{i,t-k} + \sum_{\ell=0}^{q-1} \tilde{\Lambda}_{i\ell} \Delta \mathbf{x}_{i,t-\ell}^* + \sum_{\ell=0}^{r-1} \tilde{\Upsilon}_{i\ell} \Delta \mathbf{d}_{i,t-\ell} + \mathbf{u}_{it} \quad (4)$$

If it is correctly specified, the VECM is preferred to the difference-stationary VAR since the former generates more efficient estimates. However, the presence of unpredictable structural breaks hinders this task. Thus, we decided not to pursue the VECM specification.

Second, we have sequentially searched for one and only one significant “shift in intercept” event for each equation, which is one form of a structural break, by t -test. For this purpose, first, we search for the most significant intercept-shifts for each equation, by trimming the both 20% edges of the sample period. After detecting the most significant intercept-shifts, we add the intercept-shift dummy variables if and only if the intercept dummy is statistically significant at a 5% level, to the model in order to control the effect of possible structural breaks.

¹³As an application of the Markov switching VAR, Inoue and Okimoto (2008) investigated the effect of Japanese monetary policy with hidden structural breaks. Using the difference-stationary VAR, they revealed the existence, the timing, and the types of structural breaks in the monetary policy effects.

4 Estimation and testing

We proceed with the following analysis:

1. Testing the unit root
2. Detecting the structural breaks
3. Selecting the final specification of the models
4. Diagnostic tests

4.1 Testing the unit root

We begin by investigating the order of integration of each variable by using the Augmented Dickey-Fuller Tests. The Akaike information criterion is used for selecting the optimal lag length. The results indicate that most of the variables in levels contain a unit root, but are stationary after a first differencing.

4.2 Detecting the structural breaks

The presence of structural breaks sometimes cast questions about the validity of the estimated results. In the present case, any improper treatment of outliers might seriously bias the shape of the impulse response functions. A fully flexible treatment of the structural breaks should consider such aspects as: 1) the timing of the occurrence, 2) the number of occurrences in the sample period, and 3) the types of changes, such as the intercept changes and/or the slope changes in the regression context. For our current application, the full-fledged treatment of the structural break is formidable due to the number of equations and the number of variables in each equation. Thus our proposed treatment is quite conservative. One remedy is to add an intercept-shift dummy variable, which is supposed to explain a hidden dominant change of the data, if any. However, finding a good reason for adding such dummies is also controversial. Besides, given a large number of equations, it is almost an

impossible task to examine such validities. Thus, ideally, we would like to detect and remove intercept-shifts automatically.

More specifically, we have adopted the following steps to detect and remove the intercepts-shifts.

1. Create a set of step-indicator dummy variables for the 20% to the 80% of the sample period. Since our estimation period is 1980Q2 to 2014Q3, and the number of sample period is $T = 138$, we have created approximately 80 step-indicator dummy variables;
2. Estimate the parameters of the GVAR model along with a step-indicator dummy one at a time, and save the t -value of the step-indicator coefficient. Repeat this for all the step-indicator dummy variables;
3. Choose the most significant step-indicator coefficient for each equation. If the t -value is significant at a 5% level, then add the step-indicator dummy to the GVAR model. Otherwise, discard.

This algorithm was run equation-by-equation with all the lag combination of p , q , and r , and seven combinations of three commodity prices. In order to reduce the total number of parameters, we restrict the maximum lag length of foreign variables, q , to two, and that of global variables, r , to one. Further, we restrict the maximum lag lengths of domestic variables, p , to three. The list of the detected outliers is stored, and used for selecting the final specification for each country in the next step.

4.3 Selecting the final specification of the models

As the final step, adding the detected intercept dummy variable for each equation, we re-estimate the country-specific $\text{VARX}^*(p, q, r)$ models. Given these estimates, we search for the optimal lag lengths as well as the optimal combination of commodity prices for each country by using the AIC. The results are shown in the left half of Table 5.

Table 5: Final specification of country-specific VARX*(p, q, r) models

	3 commodity model Oil, Agri, & Metal					Single commodity model Oil only				
	p	q	r	AIC	selected	p	q	r	AIC	
arg	3	1	1	707.4	O-M	3	1	1	706.4	
austlia	3	1	1	2887.9	O-A-M	3	1	1	2878.3	
bra	3	2	1	903.5	M	3	2	1	902.5	
can	3	2	1	3209.2	O-M	3	2	1	3204.9	
china	3	1	1	1850.3	A	3	1	1	1839.7	
chl	3	2	1	1577.8	O-A	3	1	1	1564.6	
euro	2	1	1	3344.0	O-M	2	1	1	3335.2	
india	3	1	1	1905.4	M	3	1	1	1894.4	
indns	3	1	1	1295.4	A	3	1	1	1285.3	
japan	3	1	1	2945.9	A-M	3	1	1	2938.4	
kor	3	2	1	2558.9	A	3	2	1	2553.1	
mal	3	1	1	2043.7	O-A-M	3	1	1	2037.3	
mex	3	2	1	1366.2	O-A	3	2	1	1364.1	
nor	2	2	1	2743.8	O-A-M	2	1	1	2726.9	
nzld	3	2	1	2662.9	M	3	1	1	2657.5	
per	3	2	1	859.9	O-M	3	2	1	858.8	
phlp	3	1	1	1659.9	O-A	3	1	1	1659.4	
safric	2	1	1	2650.3	O-A	2	1	1	2639.9	
sarbia	2	1	1	1443.1	O-A-M	2	1	1	1441.8	
sing	2	1	1	2100.5	O-A	2	1	1	2089.9	
swe	3	1	1	2826.8	O-A-M	3	1	1	2810.3	
switz	3	2	1	3120.8	O-A	3	2	1	3112.2	
thai	2	1	1	1735.0	O-A	2	1	1	1729.3	
turk	3	2	1	1216.8	A	3	2	1	1214.6	
uk	2	1	1	3128.2	O-M	2	2	1	3120.7	
usa	3	1	na	3230.6	O-A-M	3	1	na	2817.1	

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The specification used is Equation (4), where p =lag length of domestic variables (maximum lag is three), q =lag length of foreign variables (maximum lag is two), and r =lag length of global variables(maximum lag is one). $AIC = \log \mathcal{L} - (\text{number of parameters})$. Each model includes at most one automatically detected intercept-shift dummy, at the significance level of 5 percent. A column labelled “selected” reports the set of commodity prices included in the final version of VARX* models, where O, A, and M means the oil, agriculture, and metal prices, respectively. For the US, the commodity prices are treated as its endogenous variables, thus the value of r is not available (na).

4.4 Diagnostic tests

The country-specific VARX*, Equation (4), includes the contemporaneous values of $\mathbf{x}_{it}^*$ and $\mathbf{d}_{it}$, on its right hand side. We investigate two issues relating to them in this subsection. One is about the weak dependence of the idiosyncratic shocks, which is a key assumption for the estimation of Equation (4). The second issue concerns the contemporaneous impact of foreign variables on the domestic counterparts.

In the literature of GVAR, it is a common practice that the country-specific VARX* models, Equation (4), i.e. the equations of $\mathbf{x}_{it}$, are estimated on a country-by-country basis. As listed in Table 1, the commodity prices $\mathbf{d}_{it}$ are part of $\mathbf{x}_{US,t}$, even though they are treated as exogenous in the small-open economies. Thus, Equation (4) specifies dynamics of the domestic variables $\mathbf{x}_{it}$ as well as the commodity prices $\mathbf{d}_{it}$. On the other hand, the dynamics of $\mathbf{x}_{it}^*$ is not estimated, but defined by Equation (3). Practically, this enables us to reduce the number of parameters significantly, and make us construct the world model.

Three justifications for this estimation procedure are given by Pesaran, Schuermann, and Weiner (2004). They are: 1) stability of the system; 2) smallness of weights $\omega_{ij}(t)$; and 3) the weak dependence of the idiosyncratic shocks.¹⁴ Here, we examine the weak dependence of the idiosyncratic shocks. Table 6 reports the average pair-wise cross-section correlations for the levels and first differences of $\mathbf{x}_{it}$, as well as the associated VARX* residuals.

Generally speaking, the average pair-wise cross-section correlations are high for the “Levels”, but they drop drastically as differenced. The correlations further decline as their dynamics are modeled by VARX*. A closer look reveals that the VARX* model with the contemporaneous “star” variables (Type-2) generally yields much weaker dependence of idiosyncratic shocks than that without the contemporaneous “star” variables (Type-1). This is consistent with the idea that the contemporaneous “star” variables function as proxies for the common global factors. Thus, once country-specific models are formulated as being

¹⁴The stability of the system is numerically confirmed when the impulse response analysis is examined in the latter section. The smallness of weights calculated from the trade flow data is reported elsewhere, thus we do not repeat it. Concerning the weak dependence, see Appendix for additional discussion.

conditional on foreign variables, the remaining shocks across countries becomes weak, as expected.

Next we examine the contemporaneous effects of foreign variables on their domestic counterparts. Because the data are either log-differenced (for the real GDP, inflation, real equity prices, and the exchange rate) or differenced (for two kinds of interest rates), one can interpret the estimate as impact elasticity. Table 7 reports these estimates. The number of asterisks indicates the level of statistical significance.

As for the statistically significant coefficients, all coefficients for short-term interest rates are positive, as expected. For real output, the Asian countries are relatively less sensitive to foreign demand since none of the coefficients is statistically significant even at a 10% level. Concerning inflation, the significant foreign effects on Australia, China, Malaysia, New Zealand and Singapore are observed. This might reflect the degree of openness of these economies, however further investigation is needed. Noticeably, all the coefficients of equity prices are positive and significant at the one percent level. For two interest rates, similar phenomena are observed. The fact that the impact elasticities of equity prices and the long-term interest rates exhibit highly significant coefficients might reflect the degree of financial integration. On the other hand, the insensitivity of short-term interest rates for several countries is due to their monetary policies. Except for Australia, New Zealand and Singapore, the elasticities of short-term interest are insignificant for all the Asian countries.

5 Impulse response analysis

5.1 The Chinese impact

In this section, we estimate the GIRFs using the estimated GVAR model. The concept of GIRFs was proposed by Koop, Pesaran, and Potter (1996) and has been applied to VAR analysis by Pesaran and Shin (1998).

Table 6: Average pair-wise cross-section correlations of variables using in GVAR model and associated model's residuals

	real GDP				inflation				real equity prices			
			VARX* Res				VARX* Res				VARX* Res	
	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2
arg	0.91	0.08	-0.03	-0.02	0.29	0.05	0.06	0.03	0.46	0.23	0.15	-0.01
austlia	0.97	0.14	0.10	0.06	0.33	0.09	0.08	0.03	0.79	0.54	0.45	0.06
bra	0.96	0.15	0.06	0.04	0.25	0.02	0.00	-0.05				
can	0.97	0.20	0.04	0.00	0.41	0.14	0.07	0.01	0.73	0.55	0.45	0.04
china	0.97	0.09	0.03	0.04	0.13	0.06	0.03	-0.01				
chl	0.97	0.14	0.05	0.05	0.39	0.05	0.04	0.03	0.77	0.34	0.33	0.08
euro	0.96	0.25	0.13	0.10	0.44	0.16	0.10	0.02	0.75	0.56	0.49	-0.09
india	0.97	-0.02	-0.01	-0.01	0.16	0.04	0.05	0.04	0.76	0.32	0.25	0.02
indns	0.97	0.10	0.01	0.01	0.03	0.05	0.04	0.03				
japan	0.89	0.15	0.05	0.05	0.35	0.09	0.05	0.05	0.29	0.44	0.28	-0.08
kor	0.96	0.15	0.09	0.07	0.35	0.06	0.04	0.04	0.71	0.38	0.28	-0.03
mal	0.97	0.20	0.06	0.05	0.26	0.11	0.08	0.04	0.62	0.40	0.37	0.04
mex	0.97	0.16	0.06	0.04	0.23	0.00	0.03	0.02				
nor	0.96	0.09	0.06	0.05	0.37	0.08	0.06	0.02	0.80	0.50	0.39	0.08
nzld	0.96	0.14	0.08	0.08	0.32	0.07	0.08	0.04	0.40	0.41	0.32	0.03
per	0.88	0.06	0.02	0.02	0.26	-0.04	-0.02	-0.03				
phlp	0.95	0.06	0.02	0.00	0.21	0.02	0.01	0.02	0.72	0.36	0.30	0.03
safric	0.95	0.19	0.07	0.07	0.33	0.04	0.02	0.01	0.77	0.47	0.38	0.10
sarbia	0.91	0.03	0.04	0.03	-0.01	0.01	0.05	0.05				
sing	0.97	0.20	0.11	0.09	0.20	0.05	0.07	0.03	0.74	0.54	0.48	0.03
swe	0.97	0.20	0.12	0.08	0.45	0.10	0.09	0.03	0.77	0.51	0.44	-0.01
switz	0.97	0.20	0.09	0.07	0.41	0.10	0.09	0.04	0.78	0.54	0.45	0.02
thai	0.95	0.14	0.05	0.03	0.28	0.06	0.02	0.00	0.65	0.40	0.34	0.06
turk	0.97	0.14	0.03	0.03	0.16	-0.01	0.00	-0.02				
uk	0.96	0.19	0.08	0.04	0.44	0.10	0.08	0.04	0.77	0.56	0.49	-0.01
usa	0.97	0.21	0.09	0.04	0.40	0.18	0.08	0.01	0.77	0.54	0.43	-0.01

	real exchange rate				short-term interest rate				long-term interest rate			
			VARX* Res				VARX* Res				VARX* Res	
	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2
arg	0.37	0.09	0.05	0.04	0.45	0.03	0.05	0.01				
austlia	0.83	0.37	0.23	0.22	0.62	0.13	0.12	0.05	0.89	0.38	0.30	0.04
bra	0.79	0.21	0.11	0.10	0.43	0.01	0.04	-0.03				
can	0.81	0.32	0.15	0.13	0.67	0.18	0.14	0.11	0.91	0.36	0.31	-0.03
china	0.53	0.09	-0.01	-0.03	0.56	0.07	0.04	0.03				
chl	0.76	0.29	0.14	0.15	0.63	0.02	0.00	0.00				
euro	0.80	0.35	0.24	0.25	0.68	0.17	0.10	0.06	0.89	0.44	0.34	-0.08
india	0.61	0.26	0.12	0.10	0.30	0.10	0.07	0.06				
indns	0.35	0.22	0.12	0.12	0.26	0.07	0.06	0.05				
japan	0.72	0.16	0.11	0.11	0.62	0.03	0.02	0.02	0.86	0.26	0.21	-0.06
kor	0.80	0.30	0.15	0.12	0.63	0.05	0.02	0.04	0.83	0.04	0.00	-0.05
mal	0.76	0.30	0.17	0.15	0.50	0.06	0.02	0.05				
mex	0.73	0.10	0.01	0.00	0.52	0.02	0.03	0.03				
nor	0.82	0.39	0.24	0.24	0.63	0.05	0.00	-0.01	0.88	0.31	0.23	0.01
nzld	0.83	0.37	0.23	0.21	0.59	0.06	0.08	0.02	0.81	0.19	0.11	0.03
per	0.76	0.06	0.04	0.06	0.44	0.04	0.07	0.05				
phlp	0.82	0.18	0.13	0.14	0.64	0.09	0.09	0.06				
safric	0.71	0.32	0.18	0.17	0.54	0.11	0.06	0.04	0.68	0.21	0.14	0.01
sarbia	0.67	0.08	0.04	0.04								
sing	0.83	0.38	0.24	0.24	0.60	0.08	0.07	0.04				
swe	0.78	0.35	0.21	0.20	0.70	0.09	0.04	0.01	0.91	0.40	0.31	0.04
switz	0.82	0.31	0.22	0.25	0.54	0.09	0.06	0.02	0.81	0.36	0.27	0.03
thai	0.82	0.30	0.20	0.19	0.62	0.11	0.09	0.06				
turk	0.81	0.22	0.14	0.10	0.34	0.05	0.04	0.00				
uk	0.78	0.33	0.19	0.18	0.69	0.15	0.09	0.05	0.90	0.40	0.30	-0.02
usa					0.62	0.10	0.06	0.04	0.88	0.40	0.33	-0.01

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. VARX* Res (Type-2) refers to residuals from country-specific VARX* models. The specification is given as Equation (4). VARX* Res (Type-1) are obtained after re-estimating the model without the contemporaneous “star” variables.

Table 7: Contemporaneous effects of foreign variables on domestic counterparts by countries

	real GDP	inflation	real equity prices	short-term rate	long-term rate
arg	0.106	-1.701	1.095 ***	2.195	
austlia	-0.007	0.625 **	0.854 ***	0.468 ***	1.039 ***
bra	0.037	6.563 **		-5.325 *	
can	0.164 ***	0.677 ***	0.950 ***	0.524 ***	1.012 ***
china	0.096	0.403 *		0.015	
chl	0.071	0.091	0.762 ***	0.160 *	
euro	0.090 *	0.203 **	0.998 ***	0.065 ***	0.694 ***
india	0.030	0.335	0.609 ***	-0.045	
indns	0.114	-0.334		0.649	
japan	-0.006	-0.202	0.638 ***	-0.040	0.504 ***
kor	0.026	0.359	0.988 ***	-0.238	-0.069
mal	-0.012	0.447 *	1.350 ***	-0.042	
mex	0.090	-0.770		0.764 **	
nor	0.099	0.642	1.071 ***	0.232	0.733 ***
nzld	0.037	0.617 ***	0.729 ***	0.811 **	0.439 **
per	-0.079	-1.065		0.483	
phlp	-0.044	-0.323	0.905 ***	0.305	
safrs	0.012	-0.074	0.813 ***	0.017	0.542 **
sarbia	0.332 **	-0.033			
sing	0.087	0.419 **	1.317 ***	0.293 *	
swe	0.399 ***	0.896 ***	1.117 ***	0.481 ***	0.907 ***
switz	0.114	0.581 ***	0.899 ***	0.245 ***	0.510 ***
thai	0.059	0.294	0.870 ***	0.449	
turk	-0.032	1.823		1.014 *	
uk	0.077 **	0.396 **	0.813 ***	0.242 **	0.777 ***
usa	0.143 ***	0.357 ***			

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. White's heteroskedasticity robust standard error is used. ***, **, *, represent 1 percent, 5 percent, and 10 percent significance levels, respectively.

Mathematically, it is defined as

$$\mathcal{GIRF}(\mathbf{x}_t : u_{ilt}, n) = \mathbb{E}[\mathbf{x}_{t+n} | u_{ilt} = \sqrt{\sigma_{ii, \ell \ell}}, \Omega_{t-1}] - \mathbb{E}[\mathbf{x}_{t+n} | \Omega_{t-1}] \quad (5)$$

where $\sigma_{ii, \ell \ell}$ is the corresponding diagonal element of the residuals' variance-covariance matrix $\Sigma_{\mathbf{u}}$; Ω_{t-1} is the information set at time $t - 1$.

GIRFs are different from the standard IRFs proposed by Sims (1980), which assumes orthogonal shocks. The standard IRFs are calculated using the Cholesky decomposition of the covariance matrix of reduced-form errors. Thus, if we calculate the IRFs using different orders of variables, the shape of the IRFs will be different. If a VAR contains two or three variables, we might be able to use the standard IRFs by assuming a relation between the variables inferred from economic theory. However, the same approach is not useful for the GVAR model since it contains a large number of variables. This means that we cannot list a

Figure 3: GIRFs for a one percent decline in China's GDP growth rate

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the responses of 1985(*red dots*), 1995(*short dash*), 2005(*long dash*), and 2013(*line*).

set of variables with a reasonable order that reflects economic theory. Therefore, instead of using the standard IRFs proposed by Sims (1980), we use the GIRFs, which produce shock response profiles that do not vary for different orders of variables.

We will investigate how a negative real GDP shock in China transmits to the Asian countries as well as major developed economies based on the trade weights of 1985, 1995, 2005, and 2013. As explained in Section 2, as the trade linkages strengthen, we see a significant shift in the trade weight matrices of 2005 and 2013 from those of 1985 and 1995. Our focus is on seeing how the change of trade relations affects the propagation of shock.

First, we will examine the impact of a one percent drop in China's real GDP growth rate on the developed nations of the United States, the Eurozone, and Japan, see the first row

of Figure 3. The first panel shows the evolution of the Chinese GDP growth rate after a one percent decline. Possibly due to the feedback effect, a one percent decline in the GDP growth rate results in 1.6% reduction of the real GDP in levels after 20 quarters for China. For the United States, the Eurozone, and Japan, the impact of a negative shock on Chinese GDP is increasingly negative as we use more recent trade weights. However, the GIRFs have a negative shape when using the trade weight matrices of 1985 and 1995, and these lines are near zero. Therefore, it may imply that a negative Chinese shock would have had minimal or nonexistent effect on these economies in 1985 and 1995.

In terms of the magnitude, we notice that the US experiences the most pronounced impact compared to the Eurozone and Japan both in the short-term as well as the long-term. In the long-term, the size of US GDP drops by 0.07%. On the other hand, for the Eurozone and Japan, the size drops by approximately 0.05%. In terms of scale, the recent impact is approximately 12 times bigger than that of 1985 for the US and the Eurozone. For Japan, it is about 20 times bigger. Thus, we conclude that, over three decades, the US and Eurozone exhibit similar responses both qualitatively and quantitatively. We will test the significance of the negative impact in the next section.

The second to fourth rows of Figure 3 show the GIRFs for a one percent decline in China's growth on our set of Asian countries. As in the developed countries' case, the impact of a negative shock has become progressively negative on the Asian economies using more recent trade weight structures. The Republic of Korea, Malaysia and Singapore had a nearly non-existent impact with 1985 trade weight. Similar phenomena, but a slightly negative impact, are observed for other countries.

Under more recent trade structures, every country except the Philippines experiences a negative shock either in the short term or in the long term; however, the level and extent of the shocks differ greatly. Indonesia is by far the most negatively impacted country both in the short term as well as the long term. It is followed by Thailand (-0.095% in the long term), the Republic of Korea (-0.070%), Singapore (-0.050%), Malaysia (-0.050%), and

Australia (-0.045%). The impact of a negative Chinese real GDP shock is less marked for India (-0.018%). Interestingly, for the Philippines, the impact of a negative Chinese shock is positive.

In the last three panels of Figure 3, we display the GIRFs for a one percent decline in China's GDP on three commodity price indices. China's increasingly commodity-intensive growth path manifests itself in the increasingly negative impact of Chinese negative growth shock on commodity prices. Similar to the GIRFs observed above, the impact of Chinese negative GDP shock is considerably more visible under the 2013 trade matrix structure. China is the world's largest consumer of industrial metals (-1.33% drop in a long term) and the second-largest consumer of oil (-1.14%). China's impact on agricultural prices rose significantly after year 2000, although the impact on prices in both the short-term and the long-term is much more muted compared to the impact on oil and metal prices.

Figure 4 shows the GIRFs for a one percent decline in China's real GDP growth rate using the trade weights of 2013 at a 68% confidence interval using a bootstrapping method. The figures show that the GIRFs of US, Euro, Japan, Indonesia, the Republic of Korea, Malaysia, Singapore and Thailand are significant at a 68% confidence interval.

Figure 5 compares the distribution of GIRFs with different trade weights. When we use the trade weight matrix of 1985, the distribution of GIRFs stays close to the zero line for all of the sample countries. However, with 2013 trade weights, we observe significant downward shifts for the US, the Eurozone, Japan, Indonesia, Malaysia, Singapore and Thailand. For Australia, India and the Republic of Korea, the dominant portion of the distribution has also shifted downward. However, for the Philippines and New Zealand, the effect of a Chinese shock is not very clear. We have summarized the patterns in Table 8.

Lastly, we also note that oil, metal and agricultural price indices are consistently all negatively significant.

What is the response of other domestic variables? Figures 6 and 7 report the GIRFs of three other variables, Dp (rate of inflation), eq (real equity price), and $reer$ (real effective

Figure 4: Bootstrapped GIRFs for a one percent decline in China's growth using the trade weights of 2013

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the paths of standard GIRF (*blue*), median (*red line*), and 16th and 84th percentiles (*red long dash*) of the distribution.

exchange rate). To make the figures concise and easier to understand, we have shortened the horizontal axis from 21 quarters (five years) to 13 quarters (three years), and added two vertical lines, corresponding to four quarters and eight quarters after the shock.

For the rate of inflation, it drops after a negative Chinese shock for all the countries, except Indonesia. For the equity price, the markets of most countries are negatively impacted, although there are notable differences. New Zealand is the only exception whose equity market positively responds to a negative Chinese shock. As we have obtained a positive response path for its real GDP, this might be the reason. Lastly, for the real effective exchange rate, all countries experience depreciation.

Figure 5: 68 % bands of the GIRF distributions for different trade weights

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to 16th and 84th percentiles of the distribution, calculated by the trade weights of 1985 (*red dash*), and that of 2013 (*blue line*).

5.2 Further investigations

5.2.1 The impact of a potential US GDP shock

For comparison with the impact of a potential Chinese real GDP shock, analyzed in the previous section, we will now investigate the impact of a one percent drop in US real GDP on other countries. First, we review the GIRFs of China, the Eurozone, and Japan in Figure 8. Although the response of China with the trade weights of 2013 is found to be entirely positive, which is quite counter-intuitive, the effect of the US on China becomes weaker over the sample period.

On the other hand, for the Eurozone and Japan, we note that, although the impact is

Table 8: Classification of response patterns for the Asian countries with a one percent decline in China's GDP growth rate

response patterns	countries
significantly lower	japan, indns, mal, sing, thai
mostly lower	austlia, india, kor
indeterminate	nzld, phlp

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms.

negative, the level and shape does not change across different trade matrices, which was the case for China given its growing presence in the global economy.

Figure 8 shows that a decline of the US real GDP growth rate has a negative impact on Asian countries, including New Zealand and the Philippines, which both showed a more muted response to a Chinese shock. By comparing Figure 8 with Figure 3, it is easy to infer that although the impact of a US shock will be considerably larger than a Chinese shock, the magnitude of response progressively increases reflecting China's increased economic ties and influence on Asian economies.

In Figure 9, we calculated the 68% confidence interval using a bootstrapping method contrasting the GIRFs of 2013 and 1985. The impacts on the Republic of Korea and Singapore are statistically significant at 68% confidence interval when using a trade weight matrix in 1985 and 2013. With the more recent trade structure, the response of Australia, Malaysia, the Philippines, and Thailand also becomes statistically significant. For New Zealand, the significant effect of the US is observed for four quarters after the shock. However, some of the remaining countries show a borderline statistical significance, while others are not statistically significant. In general, the distribution of GIRFs with respect to a one percent decline in US 's growth rate remains the same over the last three decades for the Asian countries. This finding contrasts with the effect of a Chinese shock. Although the US has a stronger influence on Asian economies than China, these countries are more exposed to China than ever through increased economic ties.

Figure 6: Bootstrapped GIRFs for a one percent decline in China's growth using the trade weights of 2013

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the path of median (*blue*), 16th and 84th percentiles (*red dash*) of the distribution. The horizontal axis is now shortened to three years, and two vertical lines correspond to four quarters and eight quarters after the shock, respectively. For China's equations, the real equity price is not included due to data unavailability. Thus the corresponding GIRFs are not calculated..

5.2.2 The shock propagations through metals and agricultural prices

Lastly, we re-examine the implication of adding two commodities to the standard GVAR model. As we briefly discussed, in terms of AIC, we found the benefit of selecting the best combinations out of three commodities over the oil-only model for all 26 economies.¹⁵ Here, instead, we compare the shapes of the GIRFs using the year 2013 trade weights. See Figure

¹⁵We thank comments from Joseph Zveglic and Renee Fry-McKibbin on the treatment of this issue.

Figure 7: Bootstrapped GIRFs for a one percent decline in China's growth using the trade weights of 2013

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the path of median (blue), 16th and 84th percentiles (red dash) of the distribution. The horizontal axis is now shortened to three years, and two vertical lines correspond to four quarters and eight quarters after the shock, respectively. For Indonesia's equations, the real equity price is not included due to data unavailability. Thus the corresponding GIRFs are not calculated.

10.¹⁶

The responses of the “oil-only” model appear to overestimate the impact of China's slowdown for the US, Australia, New Zealand, the Philippines, and Singapore. For example, the response of Australia was significant with the “oil-only” model, which now becomes marginally insignificant with three-commodity model. According to Table 5, the VARX* model of Australia includes all three commodity prices. This suggests the usefulness of adding two commodity prices to the GVAR model. On the other hand, for Indonesia, the

¹⁶For Argentina and Chile, the VARX* lags selected by the AIC were $p = 3$, $q = 2$, and $r = 1$, or (3,2,1). However, when the GIRFs are calculated, we could not obtain the stable solutions with them. After examining the AICs for different combinations of lags for all the countries, we noticed that the increments of AIC for Argentina and Chile from (3,1,1) to (3,2,1) were almost negligible. Thus we impose (3,1,1) for these two countries. Figure 10 is calculated under these restrictions.

Figure 8: GIRFs for a one percent decline in US's GDP growth rate

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the responses of 1985(*red dots*), 1995(*short dash*), 2005(*long dash*), and 2013(*line*).

three commodities model suggests a larger negative impact in the long-term. Although the magnitude is much smaller than that of Indonesia, the negative impact of a Chinese shock on Malaysia and Thailand are also larger with three commodity models. These results indicate the usefulness of including the multiple commodity prices in order to capture the different channels of shock transmission.

6 Conclusions and remarks

In this paper, following CPRX, we estimated a GVAR model using a time-varying trade weight matrix. China's economy has been growing fast and its presence in the global economy

Figure 9: 68 % bands of the GIRF distributions for different trade weights

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to 16th and 84th percentiles of the distribution, calculated by the trade weights of 1985 (*red dash*), and that of 2013 (*blue line*).

is expanding through trade relations. We analyzed how and to what extent the Chinese economic fluctuations affect the global economy – the Asia Pacific region in particular. After estimating the GVAR model, we calculated the GIRFs with different trade weight matrices of 1985, 1995, 2005, and 2013 in order to compare the size and timing of the shock propagations. We also calculated the 68% and 90% confidence intervals using the bootstrapping method and tested whether the estimated impacts are statistically significant.

Unlike under the earlier trade structures of 1985 or 1995, a negative shock to the Chinese real GDP has a significant impact on the surrounding countries under the more recent trade structures of 2005 or 2013. When we evaluated the impact using the trade weights of 2013, we found that a negative Chinese GDP shock impacts commodity exporters, such as Indonesia,

Figure 10: GIRFs for a one percent decline in China's GDP growth rate with and without full set of commodities

Note: Please refer to Table A1 in the Appendix for a glossary of acronyms. The lines correspond to the 16th and 84th percentiles of the “oil-only” case (*red dots*) and the “optimal combination of multiple commodities” case (*blue line*)

the most, reflecting both demand and terms of trade shocks. Export-dependent countries on the East Asian production cycle, such as Japan, Singapore, Malaysia and Thailand, are also severely affected.

A shock to the Chinese real GDP also has an impact on the international prices of not only the crude oil market but also metals and agricultural markets, showing the degree of influence of China on the global terms of trade.

With regard to the future research, we consider improvement of the trade weight matrix to be the key. In this paper, following CPRX, we used the trade weight matrix representing the linkages to different countries. However, capital inflows and outflows significantly affect

Table A1: Country Abbreviations

Name	Short name	Name	Short name
Argentina	arg	Norway	nor
Australia	austlia	New Zealand	nzld
Brazil	bra	Peru	per
Canada	can	Philippines	phlp
China	china	South Africa	safrc
Chile	chl	Saudi Arabia	sarbia
Eurozone	euro	Singapore	sing
India	india	Sweden	swe
Indonesia	indns	Switzerland	switz
Japan	japan	Thailand	thai
Korea	kor	Turkey	turk
Malaysia	mal	United Kingdom	uk
Mexico	mex	USA	usa

Note) “Eurozone” includes Austria, Belgium, Finland, France, Germany, Italy, Netherlands, and Spain.

economies. Since the measurement of closeness of countries is key for the GVAR model, we should also consider using foreign direct investment data. If we can capture the financial linkages between countries, we can, for example, analyze the impact of monetary policy changes in advanced economies on developing countries.

Appendix

Data

We obtained the data files that cover the period between 1979Q1 and 2011Q2 from the “The GVAR toolbox” website at Centre for Financial Analysis & Policy, Judge Business School, University of Cambridge.¹⁷ We have added the recent data for the period between 2011Q3 and 2014Q3 mainly based on Appendix B in Smith and Gales (2011). We used the World Bank’s commodity price data downloaded from the following website.¹⁸ We have replaced Smith’s oil price data with the World Bank’s index, and added the metal index and agriculture index. The more detailed information about the added data is available from the authors upon request.

¹⁷URL is <http://www.cfap.jbs.cam.ac.uk/research/gvartoolbox/download.html>.

¹⁸URL is <http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTDECPROSPECTS/0,,contentMDK:21574907 menuPK:7859231 pagePK:64165401 piPK:64165026 theSitePK:476883,00.html>

On the weak exogeneity

This subsection follows the example by Fisher (1993) with a slight modification. For simplicity, let both $\mathbf{x}_t$ and $\mathbf{x}_t^*$ be scalars, and consider the VAR* model for a country (without country index i)

$$\begin{bmatrix} \Delta \mathbf{x}_t \\ \Delta \mathbf{x}_t^* \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix} + \begin{bmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{bmatrix} \begin{bmatrix} \Delta \mathbf{x}_{t-1} \\ \Delta \mathbf{x}_{t-1}^* \end{bmatrix} + \begin{bmatrix} \mathbf{u}_{1t} \\ \mathbf{u}_{2t} \end{bmatrix} \quad (6)$$

One can reparameterize Equation (6) in terms of conditional and marginal models as:

$$\Delta \mathbf{x}_t = \theta_0 + \theta_1 \Delta \mathbf{x}_t^* + \theta_2 \Delta \mathbf{x}_{t-1} + \theta_3 \Delta \mathbf{x}_{t-1}^* + \zeta_t \quad (7)$$

$$\Delta \mathbf{x}_t^* = \mathbf{a}_2 + \Gamma_{21} \Delta \mathbf{x}_{t-1} + \Gamma_{22} \Delta \mathbf{x}_{t-1}^* + \mathbf{u}_{2t} \quad (8)$$

The error term of the conditional model becomes:

$$\zeta_t \equiv \mathbf{u}_{1t} - \theta_1 \mathbf{u}_{2t} \sim N(0, \Omega)$$

where $\Omega = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$ with Σ s being the corresponding covariance elements of $(\mathbf{u}'_{1t}, \mathbf{u}'_{2t})'$. Then, the parameters in Equations (6), (7), and (8) are related as:

$$\theta_1 = \Sigma_{12}\Sigma_{22}^{-1}, \quad \theta_0 = \mathbf{a}_1 - \theta_1 \mathbf{a}_2, \quad \theta_2 = \Gamma_{11} - \theta_1 \Gamma_{21}, \quad \theta_3 = \Gamma_{21} - \theta_1 \Gamma_{22}.$$

The short-run dynamic stability of the conditional model requires θ_2 in Equation (7) to be $|\theta_2| < 1$. If this restriction is not imposed, the parameters of the conditional distribution $\lambda_1 = (\theta_0, \theta_1, \theta_2, \theta_3, \Omega)$ and marginal distributions $\lambda_2 = (\mathbf{a}_2, \Gamma_{21}, \Gamma_{22}, \Sigma_{22})$ define a sequential cut between the conditional and the marginal models. Hence, weak exogeneity holds.

If the short-run dynamic stability is imposed, on the other hand, it implies $|\Gamma_{11} - \theta_1 \Gamma_{21}| < 1$ due to cross-equation restrictions. Under this circumstance, λ_1 and λ_2 are no longer variation free. However, if Γ_{21} is zero, weak exogeneity still holds.

Following this insight, we have investigated the weak dependence of idiosyncratic shocks, and confirmed that pair-wise cross-section correlations of shocks are actually very weak.

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