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Measuring the Effects of Commodity Price Shocks on Asian Economies*

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Abstract

Commodity prices have become volatile over the past two decades, and their recent sharp decline has decreased the consumer price index (CPI) inflation rates for most of the economies. While many Asian economies have benefited from low international oil and food prices, the commodity exporters have suffered. Thus, the negative impact on production through the decline of producer prices has attracted considerable attention. Given this situation, policymakers have become increasingly concerned about measuring the magnitude of oil and food price shock diffusion on a nation's various inflationary indicators. This study investigates this problem by using a global vector autoregressive (GVAR) model. Specifically, we examine the impact of a one-time hike in oil and food prices on the general price levels and production for nine Asian countries and 13 other countries, including the United States and the Eurozone. We also analyze the differences of shock propagations in the pre- and post-GFC periods. Results indicate that the increased integration and dependence on exports intensified the Asian region's vulnerability to external shocks.

Keywords: Inflation, Commodity, GVAR, Trade linkage, Asian economies
JEL classification: D23, L22, L25, M10

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1 Introduction

In April 2016, the International Monetary Fund released the most recent World Economic Outlook (WEO). In this survey, the IMF listed major macroeconomic realignments that are likely to generate substantial uncertainty in the world economy. These are: “the slowdown and rebalancing in China; a further decline in commodity prices [, …]; a related slowdown in investment and trade; and declining capital flows to emerging market and developing economies” (IMF, April 2016, first paragraph of page 1).

Commodity market prices have become volatile over the past two decades, and their recent sharp decline has decreased the CPI inflation rates for most of the economies. While many Asian economies have benefitted from low international food and fuel prices, commodity exporters have suffered. Thus, analyzing the negative impact on production through the decline of producer prices has attracted considerable attention. Given this situation, policymakers have become increasingly concerned about measuring the magnitude of oil and food price shock diffusion on a nation’s various inflationary indicators.

This study aims to examine and quantify the impact of oil and food price shock propagation on the sample countries’ various inflationary indicators and industrial production, which the IMF has listed as a second key problem in the recent WEO that influences the global economic outlook in 2016.

We examine the problem by using a Global Vector Autoregressive (GVAR) model. We extend the work by Galesi and Lombardi (2009), which primarily analyzed the European economies using data for the pre-Global Financial Crisis period, in the following four ways: 1) The sample period is extended to December 2015, thus covering the post-GFC turbulence period (beginning from January 2001); 2) The model is enriched by considering China’s role in integrating the Asian region through international trade; 3) The pass-through effects for the Headline and Core consumer price indices (CPIs), as well as the producer price index (PPI) are examined; and 4) The impact on industrial production is investigated.

The remainder of the paper is organized as follows. Section 2 analyzes the historical transition of trade linkages between the sample countries using the network analysis. Section 3 explains the GVAR modeling. Section 4 discusses the data and presents the estimation results.

Section 5 presents the generalized impulse response functions (GIRFs) and investigates the effect of external commodity price shocks on the sample countries by comparing the shapes of the GIRFs with various settings. Section 6 concludes the study.

2 The transition of trade linkages surrounding China

When we investigate the transmission of the international commodity price shock to domestic prices as well as its impact on economic activity, the underlying trade linkages between countries must play an important role. Following this intuition, we investigate the evolution of trade linkages among the sample countries.

Our dataset includes 22 economies, as listed in Table 1. Of these, nine are Asian countries—China, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, and Thailand. As it is often emphasized, the economic connections of China became much stronger after China became a member of the World Trade Organization in 2001. Thus, we calculated the trade weights (or trade shares) for each sample country. For country *i*, its trade weight $w_{ij}(t)$ with respect to country *j* at time *t* is quantified as:

$$w_{ij}(t) = \frac{\text{biateral trade flows at time } t \text{ between countries } i \text{ and } j}{\sum_{k=1}^{N} \text{bilateral trade flows at time } t \text{ between countries } i \text{ and } k} \quad (1)$$

where the “bilateral trade flow” is the sum of exports and imports between a pair of countries, obtained from the IMF's Direction of Trade Statistics. In order to smooth the short-run variation of trade data, we take a five-year moving average of trade flows.

Given the $w_{ij}(t)$ for all the sample countries for different periods, the evolution of trade linkages is visualized by using network graphs (Figures 1 and 2).

The network graph in Figure 1 is constructed by using the trade weights at the beginning of the sample period, i.e., the average weights from 2001 to 2005. From this graph, we can identify three important nodes: the US, Eurozone, and Japan. These three economies have more connecting arrows with other countries in general. For instance, the US is connected with Malaysia, and the arrow has a numeric label of 0.22. This implies that Malaysia’s average trade share with the US is 22% for the 2001–2005 period. Similarly, Philippines’ and Japan’s trade share with the US are 25% and 28%, respectively.

Similar phenomena are observed for the Eurozone. The Eurozone is also an important trading hub for Norway (46%), the UK (25%), Turkey (58%), South Africa (36%), Sweden (54%), India (25%), Chile (21%), and Brazil (29%). Regarding the Asian countries, Japan plays a similar role. Japan was an important trading counterpart for China (20%), Philippines (22%), Indonesia (23%), and Thailand (25%) at the beginning of the sample period. During this period, China's influence was limited, and Japan (23%) and Korea (21%) were the two noticeable counterparts.

Trade linkages underwent drastic changes with the trade weights at the end of the sample period, i.e., the average weights from 2011 to 2015. With the current trade linkages, China became an important hub. Currently, China's share for Korea is 31%, Japan (29%), Brazil (24%), Chile (27%), Peru (24%), and South Africa (23%). Thus, China not only took over Japan's position in the Asian network, but also extended its linkages to many Latin American countries.

As we just reviewed above, the global trade flow began to change drastically shortly after China joined the WTO in December 2001. Thus, we expect that the mechanism of how the international commodity price shock propagates in the early 2000s and in the recent years would be quite different. This implies that an appropriate econometric model should be able to specify: 1) the dynamics of domestic macroeconomic variables and the global variables of each sample country; and 2) the evolution of economic linkages between the sample countries.

For this purpose, we introduce the GVAR methodology in the next section.

3 The GVAR model

3.1 A brief literature review of the GVAR

In order to quantify the magnitude of oil and food price shock diffusion to a nation's various inflationary indicators, we use a novel time-series technique: the GVAR model, which was introduced by Pesaran, Schuermann, and Weiner (2004), Dees, di Mauro, Pesaran, and Smith (2007), and Dees, Holly, Pesaran, and Smith (2007).

In general, the GVAR model is configured by a system of country-specific VAR models, each of which is connected through the so-called "foreign" variables in each sub VARs. A key idea is that the "foreign" variables are defined as a deterministic function of the other country's domestic variables. At the time of estimating the parameters, the country-specific VAR models are estimated one-by-one by assuming that the "foreign" variables are indeed "exogenous." For the dynamic analysis, such as the impulse response analysis, the entire system is solved along with the identity equations that associate the "foreign" variables with the other country's "domestic" variables.

Due to its modeling flexibility, the GVAR model has been 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 and Girardi, 2013), and US credit supply shocks (Eickmeier and Ng, 2015). The model was also applied to examine the impact of China's recent slowdown (Gauvin and Rebillard, 2015; Inoue, Kaya, and Oshige, 2015).

By using the GVAR methodology, Galesi and Lombardi (2009) examined short-term propagations of oil and food price shocks for a set of 33 countries for the period 1999–2007. Their dataset includes the US and the UK, 12 Euro area countries, 3 Baltic countries, 13 other European countries, 2 developing Asian countries, and Saudi Arabia. Thus, the region of focus is mainly the European countries. Though the measure of "closeness" between countries $w_{ij}(t)$ defined by Equation (1) is genuinely time-varying, Galesi and Lombardi substituted the sample average trade flow data. Thus, the closeness matrix in their application is effectively time-invariant.

Our study is different from Galesi and Lombardi (2009) at least in four aspects. First, we extend the sample period to December 2015, thus covering the post-GFC turbulence period (beginning from January 2001). Second, we enrich the model by considering China's evolving role in integrating the Asia-Pacific region through international trade. This is done by replacing a time-constant w_{ij} with a time-varying $w_{ij}(t)$, calculated from a five-year moving average of trade flows. Third, we include the producer price index, and thus examine the pass-through effects for the headline and core CPIs, as well as PPI. Lastly, we investigate the recent stagnation of industrial production owing to the decline of commodity prices.

3.2 The model

The *i*-th country-specific (VAR with eXogenous variables) VARX*(p, q) model (for $i = 1, ..., N$), a building-block of the GVAR model, is specified as

$$\boldsymbol{\Phi}_i(L, p_i)\mathbf{x}_{i,t} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1}t + \boldsymbol{\Lambda}_i(L, q_i)\mathbf{x}^*_{i,t} + \boldsymbol{\Psi}_i(L, q_i)\boldsymbol{\omega}_t + \mathbf{u}_{it} \qquad (2)$$

where $\mathbf{x}_{i,t}$ represents the domestic variable vector of country *i*; $\mathbf{x}^*_{i,t}$ denotes the foreign variable vector; $\boldsymbol{\omega}_t$ represents a vector of global variables; $\boldsymbol{a}_{i0}$ and $\boldsymbol{a}_{i1}$ denote the coefficients of a constant and a time trend; p_i represents country *i*'s lag length of domestic variables; q_i represents country *i*'s lag length of foreign and global variables; L denotes the lag operator; $\boldsymbol{\Phi}_i(L, p_i)$; $\boldsymbol{\Lambda}_i(L, q_i)$, and $\boldsymbol{\Psi}_i(L, q_i)$ represent the polynomials of coefficient matrices with order p_i, q_i, and q_i; and $\mathbf{u}_{it}$ represents the idiosyncratic errors. A vector of country-specific shocks, $\mathbf{u}_{it}$, is assumed to be distributed as serially uncorrelated with zero mean and a nonsingular covariance matrix, i.e., $\mathbf{u}_{it} \sim i.i.d.(0, \Sigma_{ii})$.

The element of foreign ("star") variable vector, $\mathbf{x}^*_{i,t}$, is constructed from the other country's domestic variables in the following manner. For time *t*, let us denote the first element of country *i*'s foreign variable as $x^{*(1)}_{it}$ and the corresponding variable of country *j* as $x^{(1)}_{jt}$. They are linked by the weights, $w_{ij}(t)$, which represent the time-varying "closeness" between country *i* and country *j*.[4]

$$x^{*(1)}_{i,t} = \sum_{j=1}^{N} w_{ij}(t) \;\; x^{(1)}_{jt} \tag{3}$$

By definition, $w_{ii}(t) = 0$, and $\sum_{j=1}^{N} w_{ij}(t) = 1$ for *i* = 1, …, *N*. If the variable x_{jt} is missing for country *j*, then $\{w_{ij}(t)\}_{i=1}^{N}$ is rescaled accordingly.[5]

The dynamics of the global variables, $\boldsymbol{\omega}_t$, is specified as a following VARX(*p*, *q*) model:

$$\boldsymbol{\Phi}(L, p)\boldsymbol{\omega}_t = \boldsymbol{\mu}_0 + \boldsymbol{\Lambda}(L, q)\tilde{\mathbf{x}}_{t-1} + \boldsymbol{\eta}_t \tag{4}$$

where *p* is the lag length of global variables and *q* is the lag length of the feedback variables, $\tilde{\mathbf{x}}_t$, constructed by the country-specific domestic variables in the GVAR model. The first element of $\tilde{\mathbf{x}}_t$ is defined as

[4] In this study, we use $w_{ij}(t)$ defined by Equation (1). It is also possible to construct the weight matrix by using either import or export data only, and in this way, one can clarify the direction of causality from oil and food price shock to inflation and production. We appreciate a comment from Alexei Kireyev on this issue. See Kireyev and Leonidov (2016) for identifying different network effects.

[5] Technically, we can use a different kind of $w_{ij}(t)$ for constructing the different variables. One possibility is to use capital flow data to construct financial weights for financial variables. See Galesi and Sgherri (2009), Eickmeier and Ng (2015) for empirical example, and Smith and Galesi (2014) for econometric specifications. In this study, however, we use the same weights, which are calculated from the five-year moving averages of the annual bilateral trade flows (exports + imports) between countries *i* and *j*, obtained from the Direction of Trade Statistics.

$$\tilde{x}_t^{(1)} = \sum_{i=1}^{N} \widetilde{w}_i \, x_{it}^{(1)} \tag{5}$$

where $\widetilde{w}_i$ represents a weight in order to construct these feedback variables.[6]

When we estimate the country-specific VARX* models and the global variable's VARX model, $\mathbf{x}_{it}^*$ and $\tilde{\mathbf{x}}_t$ are constructed directly from the data. However, at the time of dynamic analysis, such as calculating the impulse response functions, the values of $\mathbf{x}_{it}^*$ and $\tilde{\mathbf{x}}_t$ are calculated internally from the forecasted values of $\{\mathbf{x}_{jt}\}$ for j=1, …, N, which are obtained by solving the system of Equations (2), (3), (4), and (5). Thus, the GVAR model can describe the interactions of variables not only within a country, but also between countries.

As we report below, the variables included in the country-specific models and the global variable model are mostly integrated of order one. This implies that, if there exists long-run equilibrium relationships among these variables, the VARX* models have their corresponding Vector Error Correction Model with eXogenous variables (VECMX*) forms. If such long-run equilibrium relations are detected, they are imposed at the time of simulating the GIRFs.

4 Estimation and testing

4.1 Data and a related specification issue

In this study, we estimate 22 country-specific VARX* models and one commodity price VARX* model, at monthly frequency.[7] Nine of them are Asian countries (China, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, and Thailand). Data are collected from the OECD.Stat database by the OECD, the International Financial Statistics by the International Monetary Fund, and CEIC Data's Global Database, which cover the periods from January 2001 to December 2015.

The vector of domestic variables, $\mathbf{x}_{it}$, in the country-specific VARX* model includes at most six variables: industrial production y_{it}(mnemonic is ip); the production price index p_{it}^P (ppi); the headline consumer price index p_{it}^H (cpiH); the core consumer price index p_{it}^C (cpiC);

[6] Unlike the weights $w_{ij}(t)$ in Equation (3), the weight $\widetilde{w}_i$ is not time-varying. In this study, $\widetilde{w}_i$ is calculated from the 2009–2011 average of the GDP (in current international PPP) obtained from the World Development Indicators of the World Bank.

[7] Since one of the economies is the Eurozone, which consists of seven countries—Belgium, Finland, France, Germany, Italy, Netherlands, and Spain—the total number of countries in our dataset is 28.

the short-term interest rate r_{it} (r); and the nominal effective exchange rate e_{it} (neer).[8] Since p_{it}^{P}, p_{it}^{C}, and r_{it} are missing for some countries, they are included when available. See Table 2 for details. For instance, the model of Saudi Arabia does not include all the three variables. Two more countries—Chile and China—do not include p_{it}^{P}. For p_{it}^{C}, the data are available only for half of the sample countries.[9]

The domestic variable vector (for *i*=1,…,*N*) is $\mathbf{x}_{it} = (y_{it}, p_{it}^{P}, p_{it}^{C}, p_{it}^{H}, r_{it}, e_{it})'$ where

$$y_{it} = 100 \times \log(\text{industrial production})$$
$$p_{it}^{P} = 100 \times \log(\text{PPI})$$
$$p_{it}^{C} = 100 \times \log(\text{core CPI})$$
$$p_{it}^{H} = 100 \times \log(\text{headline CPI})$$
$$r_{it} = \text{short} - \text{term interest rate } (\%)$$
$$e_{it} = 100 \times \log(\text{nominal effective exchange rate})$$

Before taking the logarithmic transformation, the industrial production, PPI, core CPI, headline CPI, and nominal effective exchange rate are all normalized so that the average value of the period 2009M01–2011M12 takes 100. For some countries, the monthly figures of short-term interest rate are occasionally missing. If this happens, the most recent figures are repeatedly used for extrapolation

Since one of our research interests is to investigate the pass-through of the international commodity price shocks to the domestic core inflation, we have included two CPIs in our country VAR models (See Galesi and Lombardi (2009)). However, there might be a possibility that a high correlation exists between the two CPIs. Thus, we report the correlation coefficients between Δp^{C} and Δp^{H} in Table 3.

The country with the highest correlation is Turkey, and the coefficient is 0.912. However, for other countries, the coefficients are relatively low, and the sample average of the correlations is 0.515. Thus, we decide to include two CPIs in the model.

The set of foreign variables, $\mathbf{x}_{it}^{*}$, is constructed as defined by Equation (3). As discussed

[8] For y_{it}, p_{it}^{P}, p_{it}^{H}, p_{it}^{C}, and e_{it}, we have tested if the series contains seasonal variation. After adjusting the seasonality, we have detected the outliers. See Appendix for these procedures.

[9] The list of countries that do not include the core CPI is as follows: Brazil, China, India, Indonesia, Malaysia, Peru, Philippines, Saudi Arabia, Singapore, South Africa, and Thailand.

by Pesaran, Schuermann, and Weiner (2004) and Galesi and Lombardi (2009), due to a strong correlation between domestic and foreign-specific nominal effective exchange rates, the foreign-specific nominal effective exchange rates are excluded from the country-specific VARX* models. Moreover, by reflecting the fact that the US is the only large open economy in the sample period, we assume that the foreign financial markets do not affect its economy. Thus, r_{it}^{*} is excluded from the US model. See Table 4 for details.

As for the global variables $\boldsymbol{\omega}_t$, two commodity prices, log of crude oil price index p_t^O, and log of food price index p_t^F, are included in order to capture the influences from the international commodity market. 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 5, which reports World Bank Commodity Price Index weights, the share of crude oil in the energy index is 84.6%.

Besides "energy," the World Bank publishes two more commodity indices: "non-energy commodities" and "precious metals" (See Table 5). Among the "non-energy commodities" group, the largest subcategory is "food," which constitutes 40.0% of "non-energy commodities." Since monetary authorities often pay special attention to the movement of the core CPI inflation, which usually excludes energy and food products, we have included the food price index as a second variable in $\boldsymbol{\omega}_t$.

4.2 Testing the unit root

We begin by investigating the order of integration of each variable by using the weighted symmetric Dickey-Fuller tests (Park and Fuller, 1995). The Akaike information criterion (AIC) is used for selecting the optimal lag length. The test results reported in Table 6 indicate that most of the variables in levels contain a unit root, but are stationary after a first differencing.[10]

4.3 Estimating the country-specific VARX* models

We estimated the country-specific VARX* models by setting the maximum lag lengths of domestic

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[10] We observe two exceptional cases for the headline CPI and core CPI of Turkey. After a first differencing, the unit root test statistics are -1.63 (cpiH) and -0.19 (cpiH), both of which are larger than the 5% critical value, -2.55. They become stationary after differencing twice.

variables, p, to three, and the maximum lag lengths of foreign and global variables, q, to one. The optimal length is determined by using the AIC, and the results are reported in Table 7.[11]

If there exists any co-integration relationships between $\mathbf{x}_{it}$, $\mathbf{x}_{it}^{*}$, and $\boldsymbol{\omega}_{t}$, the imposition of such long-run relations is desirable when we conduct the impulse response analysis. Thus, we estimated the co-integration rank country-by-country using the trace statistic. Table 7 reports the results (See the column titled "Original"). According to this test, 61 co-integrating vectors are found in total.

Since our treatment of the long-run relationships are atheoretical, we do not give any specific macroeconomic interpretation to the relations we found. However, since the model includes three price indices and one exchange rate, we speculate that one or two of the detected co-integrating relations correspond(s) to the purchasing power parity of the exchange rate. Thus, it is worth examining if the detected long-run relationships are strong. For this purpose, we checked the shape of the persistence profiles (PPs).

If the detected vector is indeed a co-integrating vector, the value of the PPs should converge to zero, as the horizon goes to infinity after taking one at the time of impact. The left panel of Figure 3 shows the entire 61 PPs, some of which exhibit slow convergences with an unusually large fluctuations.

We reduced the number of co-integrating vector one-by-one, referring to the value of PPs at 24 months after the shock. Among those PPs at 24 months, we examine if they take values larger than 0.10. If there exists such PP(s), then the PP with the highest value will be discarded. After this correction, the system is solved again, and a new set of PPs will be calculated. This iteration continued until all the PPs at 24 months after the shock take values less than 0.10. For our sample dataset, it took us nine iterations. Using this criterion, the number of the remaining co-integrating vectors is reduced to 52. The right panel of Figure 3 shows the PPs after this adjustment. As reported at column "Adjusted" in Table 7, we have discarded one vector from Brazil, three from the Eurozone, one from Mexico, three from the UK, and one from the US.

Based on the "adjusted" co-integration ranks, the country-specific VARX* models are transformed into the vector error correction form. We use these models to investigate the

[11] For estimation and dynamic analysis, we used the Matlab program, the GVAR Toolbox 2.0, provided by Smith and Galesi (2014).

commodity price shocks to the sample countries.

4.4 Diagnostic tests

In the GVAR literature, it is a common practice that the country-specific VARX* models, Equation (2), i.e., the equation of $\mathbf{x}_{it}$, is estimated on a country-by-country basis. 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 construct the world model.

There are several conditions that must be satisfied for this estimation procedure to be justified. First, the entire system must be stable. We have investigated the shape of persistence profiles, and the suspected unstable co-integration vectors are already eliminated. In addition, the stability of the system is numerically confirmed when the impulse response analysis is examined in the latter section.

Second, the weak exogeneity of $\mathbf{x}_{it}^*$ and $\boldsymbol{\omega}_t$ must be checked. For this purpose, the method by Dees, di Mauro, Pesaran, and Smith (2007) is used. In this test, the joint significance of the estimated error correction terms in the auxiliary equations for the country-specific foreign variables are examined. For the lags of variables in the auxiliary equations, we assume that the lag length for the domestic variables is three, and that for the foreign variables is four, for all the test equations. The test results are reported in Table 9. Out of 153 cases, the weak exogeneity assumption is rejected for five cases, which is 3.27%. Thus, we do not observe any significant violation of the weak exogeneity assumption.

Thrid, we investigate the parameter stability. Table 8 reports a series of structural break tests used in GVAR literature. Reflecting the fact that our sample includes the turbulence period of GFC, the test results exhibit a slightly higher rejection frequency of stability. However, by comparing the standard vs heteroscedasticity-robust statistics, one can infer that a part of rejection comes from breaks in the error variances, not breaks in coefficients.[12]

Lastly, we examine the weak dependence of the idiosyncratic shocks (See Pesaran, Schuermann, and Weiner, 2004). Table 10 reports the average pair-wise cross-section correlations

[12] We appreciate a comment from Alexei Kireyev for drawing our attention to the importance of parameter stability in GVAR model. As for the possible additive outliers, they are detected and removed based on a simplified procedure of Chen and Liu (1993) prior to the estimation.

for the levels and the first differences of $\mathbf{x}_{it}$, as well as the associated VARX* residuals.

In general, the average pair-wise cross-section correlations are high for the "Levels," but they drop drastically after being 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) usually yields much weaker dependence of idiosyncratic shocks than that without the contemporaneous "star" variables (Type-1). This result 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 conditional on foreign variables, the remaining shocks across countries become weak, as expected.[13]

4.5 Instantaneous effects

Next, we examine the instantaneous effects of foreign variables on their domestic counterparts. Because the data are either log-differenced (for the industrial production, three price indices, and the nominal effective exchange rate) or differenced (for the short-term interest rate), one can interpret these estimates as impact elasticities. Table 11 reports the estimates.

For industrial production, the average elasticity is 0.468 and the median is 0.333. The impact elasticity of Turkey, 1.916, is the highest, followed by Singapore, whose coefficient is 1.652, both of which are significant at 1% level. Other than these two countries, the elasticities are in general less than one. Among other Asian countries, the industrial productions of India, Korea, and Malaysia are sensitive to foreign industrial production. On the contrary, the coefficients of China, Indonesia, Japan, Philippines, and Thailand are statistically insignificant.

For producer price index, significant foreign effects are observed for many Asian countries, except for India. This might reect the value-chain relationship between these countries. Concerning the headline CPI, although we observe many statistically significant coefficients, the foreign effects on domestic counterparts are less clear. In particular, for India, Indonesia, Korea, Malaysia, and Thailand, the coefficients are negative though they are all insignificant. For the core CPI, although data availability is limited, the coefficients are insignificant for most of the countries. This might be because the fluctuation of the core CPI reects the domestic factors rather than the foreign factors.

[13] Based on this observation, we use the block-diagonal specification for the error covariance matrix at the time of bootstrapping the generalized impulse response functions.

Lastly, the coefficients of short-term interest rate are either positive and significant, as global financial integration predicts for seven countries, or insignificant reflecting the independence of the monetary authority for 13 countries.

4.6 Commodity price VARX model

Next, we estimated the inter-variable relationship between two commodity prices. For each equation, the optimal lag lengths are selected by the AIC. Since no co-integrating vector is detected by the trace test, we transform Equation (5) into a difference-stationary VARX form. The estimated coefficients as well as the error covariance matrix are as follows:

$$\begin{bmatrix} \widehat{\Delta p_t^O} \\ \widehat{\Delta p_t^F} \end{bmatrix} = \begin{bmatrix} -0.5629 \\ -0.2934 \end{bmatrix} + \begin{bmatrix} 0.1907 & 0.3941 \\ -0.0631 & 0.4535 \end{bmatrix} \begin{bmatrix} \Delta p_{t-1}^O \\ \Delta p_{t-1}^F \end{bmatrix}$$

$$+ \begin{bmatrix} -0.0382 & 0.4371 \\ \times & \times \end{bmatrix} \begin{bmatrix} \Delta p_{t-2}^O \\ \Delta p_{t-2}^F \end{bmatrix} + \begin{bmatrix} 1.4968 \\ 0.3637 \end{bmatrix} \Delta \tilde{y}_{t-1} \qquad (6)$$

$$+ \begin{bmatrix} \times \\ 1.1930 \end{bmatrix} \Delta \tilde{y}_{t-2}$$

$$E[\hat{\boldsymbol{\eta}}_t \hat{\boldsymbol{\eta}}_t'] = \begin{bmatrix} 59.167 & 8.882 \\ 8.882 & 9.282 \end{bmatrix}$$

Notice that, rather than adding a vector of feedback variables $\tilde{\mathbf{x}}_t$ to the model, we include only one feedback variable, $\tilde{y}_t$, which is the PPP-GDP weighted average of the industrial production indices. We have included this variable as a proxy of global demand.

The element of coefficient matrix with "×" indicates that the corresponding variable is dropped by AIC. Thus, the oil price equation has two lags of own and food price (in difference), and one lag of global demand (in difference). On the other hand, the food equation has one lag of prices and two lags of global demand.

F-statistics for the serial correlation test of residuals with three lags are 1.839 (for the oil price equation) and 0.292 (for the food price equation). Both of these statistics are much smaller than 2.657, the 5% significance level. Therefore, the dynamic properties of these prices are sufficiently modeled with the above specification.

The coefficient vector of $\Delta \tilde{y}_{t-1}$ implies that a 1% increase of the global industrial production rises the subsequent period's oil price by more than 1.5%. Regarding the impact of food price hike, its cumulative elasticity is estimated to be the same magnitude (1.5567% = 0.3637% +

1.1930%).

5 Impulse response analysis

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 the VAR analysis by Pesaran and Shin (1998).

Mathematically, it is defined as

$$\mathcal{GIRF}(\mathbf{x}_t:\ u_{i\ell t}, n) = E[\mathbf{x}_{t+n}|\ u_{i\ell t} = \sqrt{\sigma_{ii,\ell\ell}}, \Omega_{t-1}] - \mathrm{E}[\mathbf{x}_{t+n}|\Omega_{t-1}] \quad (7)$$

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

GIRFs are different from the standard IRFs proposed by Sims (1980), which assume 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 implies that we cannot list a set of variables with a reasonable order that reflects economic theory. Therefore, rather than 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.

In the next subsection, we will investigate how a positive oil price shock transmits to the Asian countries as well as major developed economies.

As confirmed in Section 2, China's role in international trade has changed drastically beginning from the early 2000s. In order to examine the effect of this change, we pay special attention to two sub-periods: 2001–2005 ("Period 1") and 2011–2015 ("Period 3"). Roughly speaking, China was peripheral in the trade network in Period 1, and the country became a hub in

Period 3. Moreover, as Figure 4 shows, both oil and food prices are rising in Period 1 (pre-GFC); however, they are falling in Period 3 (post-GFC).

Our aim is to analyze how the change of trade relations affects the propagation of commodity price shocks. Thus, the GIRFs in Period 1 are calculated based on the average trade weights for 2001–2005, and those in Period 2 and 3 are calculated using the average trade weight for 2006-2010 and that of 2011–2015, respectively.

5.1 The oil price shock

Figure 5 displays the plot of responses of headline CPI, p^H, among Asian countries to one standard deviation (S.D.) increase in oil price, p^O, in pre-GFC period, in GFC period, and in post-GFC period.[14] The median path and the 68% and 90% confidence intervals are constructed by using a bootstrapping method with 1,000 replications. A vertical black line in each graph corresponds to 12 months after the shock. For classification purposes, we use this vertical line to differentiate between the short- and long-term effects.

The first row of Figure 5 is the responses in pre-GFC period. The magnitude of the short-term oil price shock diffusion on headline CPI, measured in the median responses, are positive for most of the countries, except for China and India. For instance, one S.D. increase in oil price rises the headline CPI by 0.20% for Japan. For other Asian countries, Philippines respond the most (0.70%), followed by Thailand (0.58%), Indonesia (0.29%) and Singapore (0.26%). The responses of Korea (0.16%) and Malaysia (0.04%) are much smaller than that of Japan. For India (-0.12%) and China (-0.49%), the responses are negative.

The second and the third row of Figure 5 show the GIRF plots of the same headline CPI; however, they are calculated using the average trade weights for 2005-2010, and that of 2011–2015, respectively. Recall that the weight $\{w_i\}_{i=1}^{N}$ in the commodity price VARX model, Equation (6), is time-invariant. Thus, the standard error of oil price equation's residual, 7.692=$\sqrt{59.167}$, in Figure 5 is the same.[15] This implies that the magnitude are directly comparable.

For Indonesia, Korea, Philippines, and Thailand, we even observe positive and significant

[14] A complete set of GIRFs are available from authors upon request.
[15] The median value of one S.D. oil price shock was 7.903.

responses at the 90% confidence level for three years. However, compared with the cases in pre-GFC, the responses in post-GFC have smaller medians in general. Thus, for Japan, Malaysia, and Singapore, the responses are only significant at the 68% confidence level. For China and India, the headline CPI does not respond to the oil price shock at all.

Lastly, we summarize the responses of core CPIs. Figure 6 shows the results. The data of the core CPIs, p^C, are available for a limited number of countries. In pre-GFC period, the responses are significantly positive at the 90% level for Chile, Euro, Mexico, the UK, and the US. For Japan and Turkey, they are significantly positive at the 68% level only for the short-term. However, the images are quite different in post-GFC period. The responses of core CPI become insignificant for most of the sample countries, except Euro and the UK, which exhibits a clear positive increase even at the 90% confidence level. For Japan, though the median response is slightly positive even after three year period, indicating a drop in oil price has a slight long-run deflationary pressure, its 16th percentile crosses zero line shortly after the shock. Thus the currently observed decline of oil price has a limited effect to the deflation in Japanese economy.

5.2 The food price shock

We also examined the responses of headline CPIs to a food price shock. The size of a common shock, measured by the standard error of food price equation's residual, is $3.046=\sqrt{9.282}$. Recall that the standard error of oil price model's innovation is 7.692. Thus the common innovations of the food price index is less than a half of that of oil price index. Results are illustrated in Figure 7.

In pre-GFC period, the responses of headline CPIs to the food price shock in Figure 7 resemble those to the oil price shock in Figure 5, both in the shape and in the magnitude. However, noticeable differences are observed for Korea. For Korea, one S.D. food price shock rises the long-term median inflation approximately twice compared to one S.D. oil price shock.

Likewise, in post-GFC period, the pattern of responses to a food price shock is very similar to the one we obtained for the case of oil price shock. For India, the headline CPI does not respond to the food price shock at all. For China, Indonesia, and Japan, however, the food price shock significantly rises the inflation at the 90% level for the short-term.

The pattern of the core CPI responses to the food price shock, illustrated in Figure 8, is almost the same as that of those to the oil price shock, for both trade weights. For Japan and Korea, they exhibit very different results. For Japan, though the median response paths are slightly positive in both periods, the core CPI does not show any statistically significant response to the food price shock. On the other hand, for Korea, the response is significant at the 90% level for the short-term in pre-GFC period, and is even more significant for the long-term in post-GFC period. This indicates that the recent Korean economy is more vulnerable to the shock in food price rather than that of oil price.

5.3 The responses of producer price index

Third, we investigated the responses of producer price indices, as shown in Figure 9. The PPIs are not included in the model of Galesi and Lombardi (2009), since they focused on the pass-through of commodity price hike to the consumer price index. However, we included the PPIs to our model in order to analyze the recent problem of declining PPIs due to fall of commodity prices.

Unlike the case of CPIs, we observe positive, significant and persistent responses at the 90% level for all the countries, except for India, in pre-GFC period. Even for India, it exhibit the positive response for at least one year. Among the Asian countries, Singapore shows the highest short-term sensitivity. In Period 1, the PPI has inflated by 2.87% in 12 month after the shock, and 3.40% in three years. It is followed by Philippines (2.54% for the short-term; and 3.56% for the long-term), Thailand (2.27% and 2.88%), Indonesia (1.74% and 2.17%), and Malaysia (1.47% and 1.16%). For Korea and Japan, the responses are slightly lower than 1%.

Unlike the cases of core CPIs and headline CPIs, the responses of PPIs are significantly positive for most of the sample countries in post-GFC period. Though the responses of India is not significant at some horizon, its median response is still positive.

5.4 The responses of industrial production

Lastly, we examine the impact of the oil price hike on industrial production, y. The importance and influence of crude oil price fluctuations on the macroeconomic variables of countries, such as the US, have been reported by numerous researchers. Examples include Hamilton (1983, 1996, 2003), Hooker (1996), and Cunado and de Gracia (2005).

As illustrated in Figure 10, the oil price shock negatively impacted the industrial production for most of the sample countries in pre-GFC period. On the contrary, the industrial production of the oil-producing countries, such as Brazil, Indonesia, and Saudi Arabia, have been positively impacted. These results in Figure 10 are consistent with the previous literature on oil price shocks.

However, the responses in post-GFC period are distinctively different from the ones in pre-GFC period. Surprisingly, for many non oil-producing countries, the median responses are not negative but "positive," and for some countries, they are even significant for a short term. This tendency is observed for many Asian countries, including China, India, Korea, Malaysia, Philippines, Singapore, and Thailand.

Recall that, when we calculated the GIRFs for three subperiods, we used the same estimated parameters of the GVAR model. Thus, the difference of the GIRFs across subperiods comes solely from the difference of trade weights, which are used for each calculation.

Results in this section indicate that the oil price hike had a negative impact for the non-oil producing countries with the trade linkages of pre-GFC period, as theory suggests. However, this causal relation from an oil price hike to a stagnation of industrial production has reversed, at least for a short time period, for many sample countries with the trade linkages of post-GFC period.

As we are currently suffering from a drop of commodity prices, this response pattern implies that the decline of commodity prices reduces industrial production at least for a short period.

6 Conclusions and remarks

China's membership of the World Trade Organization in 2001 drastically changed the country's role in the international trade network. The emergence of the Chinese economy reformulated not only the Asian trade network, but also the trade flows with respect to many Latin American countries. Through this transformation, the price transmission mechanism from raw materials to intermediate goods, and to the final goods must have undergone a change. Based on this intuition, we investigated the impact of oil and food price shocks to CPIs, PPIs, and industrial production for 22 countries.

The inflationary impacts of commodity price shocks on headline CPIs are confirmed for many sample countries. Although a direct comparison with the results by Galesi and Lombardi (2009) is not possible due to a difference in sample countries and sample periods, our findings about CPIs in pre-GFC period, which overlaps the sample period of Galesi and Lombardi, are consistent with theirs in general for both oil and food price shocks.

However, when we investigated the recent price response patterns in post-GFC period to an oil price shock, the responses have smaller medians in general. Among Asian countries, we observe positive, persistent, and significant responses at the 90% level for Indonesia, Korea, Philippines, and Thailand. However, for Japan, Malaysia, and Singapore, the responses are only significant at the 68% level. For China and India, the headline CPI does not respond to the oil price shock at all.

The responses of the headline CPIs to a food price hike resemble those to the oil price shock, both in the shape and in the magnitude of the GIRFs. However, among Asian countries, Korea seems to be an exception. The long-term median headline CPI in from the food price shock is twice as big as that by the oil price shock. Also the response of core CPI are significant and persistent. This indicates that the Korean economy is more vulnerable to the shock in food price rather than that of oil price.

Since the difference of the GIRFs for three subperiods comes solely from the difference of trade weights used for each calculation, the results indicate that trade linkages play a significant role in the propagations of commodity price shocks.

Concerning the PPIs, we have just reported the case of oil price hike. Unlike the case of CPIs, the responses are positive and significant for many countries across subperiods. This implies that the surge of oil price has generated a inationary pressure to a nation's PPI in pre-GFC period, and on the contrary, the recent decline in commodity prices has a deationary impact on the PPIs in post-GFC period.

Lastly, we investigated the impact of oil price hike on industrial production, and observed a clear negative impact in pre-GFC period, as theory predicts. However in post-GFC period, we observed many positive median responses, and some of them are even significant for a short term. Thus, the implication of oil price hike has drastically been changed, and this suggests that a change in trade linkages is a possible cause of the recent downward co-movement between commodity prices and industrial production.

In the future, it is worth examining the effect of the financialization of commodity prices. As Tang and Xiong (2012) analyzed, commodity prices had little co-movement with stocks prior to the early 2000s. However, through the financialization of commodities, their correlations have increased. This implies that the causal relation between the oil price and industrial production might also have undergone a change. This suggests a possibility of extending the GVAR model with time-varying parameters.

Appendix about data construction

We constructed the country data that covers the period between January 2000 and September 2015 by compiling the OECD statistics data, the IMF e-library data, the BIS's website (effective exchange rate), and CEIC Data's Global Database. Where the recent figures are missing in these database, we obtained data from governments' or central banks' websites.

As for China's industrial production series, the non-seasonally adjusted level data (from CEIC) was available only for the period from January 2011 to September 2015. For the period from January 2000 to December 2010, the series was extrapolated using the "Percent Change over Previous Year" series obtained from IFS (Code: 92466..XZF...; IFS CD-ROM, June 2015 version). The extrapolated data exhibits a strong and unique seasonal fluctuation. This is due to the phenomenon called "moving-holidays" of the Chinese New Year, stemming from the difference between the Lunar and the Gregorian Calendars. We have used a simple correction method described in Roberts and White (2015).

For series y_{it}, p_{it}^{P}, p_{it}^{H}, p_{it}^{C}, and e_{it}, seasonal fluctuations are detected and adjusted by the method explained in Appendix B of Smith and Galesi (2014). For the first difference of series, y_{it}, p_{it}^{P}, p_{it}^{H}, p_{it}^{C}, and e_{it}, the additive outliers are detected and corrected prior to the estimation. See Chen and Liu (1993) for details. We use three standard deviations as a threshold. Two commodity prices are obtained from the World Bank's commodity price data downloaded from the following website: http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTDECPROSPECTS/0,,contentMDK:21574907 menuPK:7859231 pagePK:64165401 piPK:64165026 theSitePK:476883,00.html.

More detailed information about the added data is available from the authors upon request.

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Table 1: A list of sample countries and their abbreviations

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

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

Table 2: List of domestic variables

	ip	ppi	cpiH	cpiC	r	neer
brazil	○	○	○		○	○
canada	○	○	○	○	○	○
chile	○		○	○	○	○
china	○		○		○	○
euro	○	○	○	○	○	○
india	○	○	○		○	○
indonesia	○	○	○		○	○
japan	○	○	○	○	○	○
korea	○	○	○	○	○	○
malaysia	○	○	○		○	○
mexico	○	○	○	○	○	○
norway	○	○	○	○	○	○
peru	○	○	○		○	○
philippines	○	○	○		○	○
saudi_arabia	○		○			○
singapore	○	○	○		○	○
south_africa	○	○	○		○	○
sweden	○	○	○	○	○	○
thailand	○	○	○		○	○
turkey	○	○	○	○	○	○
uk	○	○	○	○	○	○
usa	○	○	○	○	○	○

Note: A circle indicates that the data is available. If blank, then this indicates that the corresponding variable is not available, and is thus excluded from the dataset.

Table 3: Correlation coefficients of Δp^C and Δp^H

belgium	0.669	mexico	0.497
canada	0.251	netherlands	0.524
chile	0.562	norway	-0.071
finland	0.619	spain	0.544
france	0.563	sweden	0.314
germany	0.637	turkey	0.912
italy	0.596	uk	0.714
japan	0.711	usa	0.267
korea	0.443		

Table 4: Set of variables used for the GVAR odels

	Country-Specific VARX*		Commodity VAR		
	domestic	foreign	global	own	feedback
	$\mathbf{x}_{it}$	$\mathbf{x}_{it}^*$	$\boldsymbol{\omega}_t$	$\boldsymbol{\omega}_t$	$\tilde{\mathbf{x}}_t$
industrial production	y_{it}	y_{it}^*			$\tilde{y}_t$
producer price index	p_{it}^P	p_{it}^{P*}			
consumer price index (headline)	p_{it}^H	p_{it}^{H*}			
consumer price index (core)	p_{it}^C	p_{it}^{C*}			
short-term interest rate	r_{it}	r_{it}^*			
nominal effective exchange rate	e_{it}				
oil price			p_t^O	p_t^O	
food price			p_t^F		p_t^F

Note: The foreign-specific short-term interest rate, r_{it}^*, is excluded from the US's VARX* model only.

Table 5: World Bank Commodity Price Index weights, in percentage

Commodity	Share	Commodity	Share
Energy Commodity		*Non-energy Commodity*	
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
Precious Metals		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 2002-2004 developing countries' export values. November 24, 2008.

Table 6: Unit root test statistics for variables

Panel a) Unit Root Tests for the Domestic Variables

	brazil	canada	chile	china	euro	india	indonesi	japan	korea	malaysia	mexico	norway	peru	philippin	saudi_ar	singapor	south_afi	sweden	thailand	turkey	uk	usa
ip	−1.21	0.81	0.31	0.57	−3.32	1.59	0.88	−0.91	0.34	0.43	−0.44	−0.86	0.43	0.84	−1.63	−0.43	−1.68	−2.05	0.36	0.66	−1.76	−1.69
Dip	−8.42	−5.15	−12.88	−3.64	−4.57	−13.65	−9.62	−4.83	−9.20	−8.09	−5.31	−9.31	−8.15	−11.50	−7.21	−14.67	−11.83	−6.02	−7.03	−9.67	−8.07	−3.65
ppi	1.33	−0.20			−0.23	0.70	1.78	−2.28	−0.44	−0.03	0.98	−0.37	0.28	0.40		−1.01	1.74	−0.26	0.25	2.91	−0.12	−0.75
Dppi	−4.75	−7.63			−5.91	−5.85	−5.39	−4.93	−5.81	−7.39	−5.41	−9.41	−5.82	−4.96		−8.07	−9.09	−8.82	−7.12	−3.33	−3.92	−4.93
cpiH	1.68	2.10	0.95	0.26	0.87	2.30	3.18	−1.22	2.09	1.26	1.32	2.89	0.96	0.72	−0.25	0.03	0.83	0.45	0.29	1.97	1.43	1.58
DcpiH	−4.13	−8.07	−3.60	−5.39	−4.43	−8.69	−9.20	−7.99	−9.32	−4.74	−8.60	−6.81	−3.69	−4.50	−3.34	−3.55	−4.04	−3.86	−4.64	−0.90	−4.99	−8.77
cpiC		2.09	2.69		0.61			−0.37	3.19		0.83	2.37						1.05		1.90	3.12	1.65
DcpiC		−7.02	−7.49		−3.12			−7.96	−8.62		−4.03	−7.50						−9.69		0.78	−9.55	−7.68
r	−1.90	−0.93	−2.87	−2.73	−1.20	−1.67	−2.48	−2.15	−0.39	−2.96	1.42	−1.28	−2.41	1.28		−1.30	−2.26	−1.77	−2.17	3.63	−0.88	−0.73
Dr	−5.67	−5.30	−4.87	−10.15	−5.67	−11.09	−4.25	−7.13	−7.61	−5.60	−4.62	−3.53	−7.67	−4.12		−11.76	−5.17	−5.21	−5.70	−3.12	−6.85	−4.79
neer	−1.60	−0.80	−2.64	−0.87	−1.56	−0.67	0.02	−2.01	−1.66	−2.22	0.11	−0.54	−0.83	−1.57	−1.19	0.34	−0.99	−2.60	−0.94	1.86	−1.44	−1.01
Dneer	−7.86	−8.48	−8.07	−5.50	−8.65	−8.96	−7.63	−7.64	−8.74	−8.79	−7.57	−7.25	−9.95	−6.97	−8.50	−5.72	−5.88	−9.09	−5.63	−4.99	−7.97	−6.17

Panel b) Unit Root Tests for the Foreign Variables

	brazil	canada	chile	china	euro	india	indonesi	japan	korea	malaysia	mexico	norway	peru	philippin	saudi_ar	singapor	south_afi	sweden	thailand	turkey	uk	usa
ip*	−0.51	−1.23	−0.23	−0.70	−0.29	−0.34	−0.06	0.34	0.06	0.10	−1.16	−2.19	−0.19	−0.21	−0.37	0.31	−0.29	−1.85	−0.14	−1.49	−1.55	0.05
Dip*	−4.05	−3.39	−4.60	−4.48	−4.48	−4.85	−5.91	−5.08	−4.61	−6.61	−3.51	−4.07	−4.61	−5.43	−4.49	−5.44	−4.64	−5.23	−4.85	−4.10	−4.06	−4.38
ppi*	−0.20	−0.67	0.17	−0.28	0.34	−0.01	−0.53	0.01	−0.07	−0.36	−0.68	−0.12	−0.27	−0.42	−0.03	0.08	−0.12	−0.01	−0.29	−0.16	−0.02	0.52
Dppi*	−4.78	−4.86	−4.52	−5.80	−6.31	−6.19	−6.34	−6.07	−5.96	−6.60	−4.84	−6.08	−4.75	−6.09	−5.91	−6.06	−5.79	−7.04	−6.05	−5.87	−6.23	−6.44
cpiH*	1.77	1.69	1.94	1.87	1.66	1.71	1.59	1.12	0.85	1.60	1.72	1.56	1.87	1.58	2.03	1.88	1.67	1.80	1.73	1.67	1.85	0.95
DcpiH*	−7.25	−8.61	−5.55	−7.80	−4.92	−5.31	−5.03	−6.34	−5.13	−6.59	−8.60	−4.84	−7.61	−6.88	−7.10	−7.19	−6.71	−5.18	−5.22	−4.54	−4.91	−5.58
cpiC*	0.85	1.49	0.92	1.33	1.33	0.92	2.26	0.83	1.54	1.89	1.49	0.99	0.86	2.09	1.26	1.19	0.89	0.92	2.40	0.55	0.80	1.11
DcpiC*	−5.47	−7.63	−5.61	−6.21	−4.02	−5.63	−7.81	−5.03	−5.58	−7.88	−5.70	−6.00	−5.06	−8.10	−4.83	−6.45	−5.49	−5.55	−7.86	−5.15	−4.55	−6.74
r*	−0.92	−0.72	−0.80	−1.27	−0.75	−1.17	−1.37	−1.04	−1.39	−1.14	−0.78	−1.28	−1.31	−1.07	−0.89	−1.60	−1.19	−1.17	−1.30	−1.27	−1.21	−0.46
Dr*	−6.77	−4.75	−6.89	−5.12	−4.47	−5.84	−6.92	−7.71	−8.39	−7.22	−4.76	−4.85	−6.62	−6.98	−5.16	−6.74	−7.15	−4.87	−7.37	−6.27	−4.98	−4.62

Panel c) Unit Root Tests for the Global Variables

poil	−1.27
Dpoil	−7.28
pfood	−1.03
Dpfood	−6.74

Note: The weighted symmetric Dickey-Fuller test statistics are based on univariate AR(p) models in levels with optimal lag length p selected by using the AIC. For each variable, we have tested both in level and in difference. The test regressions include a constant term, and the 5% critical value is -2.55. (To Editor: Data of this table is available in EXCEL file)

Table 7: Final specification of country-specific VARX* (p, q) models

	VARX* models		Coint ranks	
	p	q	Original	Adjusted
brazil	3	1	3	2
canada	2	1	4	4
chile	2	1	2	2
china	2	1	2	2
euro	2	1	4	1
india	3	1	2	2
indonesia	2	1	2	2
japan	3	1	3	3
korea	2	1	4	4
malaysia	2	1	1	1
mexico	2	1	4	3
norway	2	1	2	2
peru	3	1	4	4
philippines	2	1	2	2
saudi_arabia	2	1	1	1
singapore	3	1	2	2
south_africa	2	1	3	3
sweden	3	1	2	2
thailand	3	1	2	2
turkey	3	1	3	3
uk	1	1	3	0
usa	2	1	6	5

Note: The specification used is Equation (2), where p = lag length of domestic variables (maximum lag is three), and q = lag length of foreign and global variables (maximum lag is one). The original cointegration ranks detected by trace statistics (at the 5% critical level), and the ranks after adjustment are reported.

Table 8: Testing for parameter stability

Variables	ip	ppi	cpiH	r	neer	cpiC
PK sup	3	5	6	3	1	5
	[13.6]	[26.3]	[27.3]	[14.3]	[4.5]	[45.5]
PK msq	2	3	4	2	2	3
	[9.1]	[15.8]	[18.2]	[9.5]	[9.1]	[27.3]
Nyblom	2	3	2	7	1	3
	[9.1]	[15.8]	[9.1]	[33.3]	[4.5]	[27.3]
Robust Nyblom	2	2	2	3	1	3
	[9.1]	[10.5]	[9.1]	[14.3]	[4.5]	[27.3]
QLR	3	5	6	16	5	5
	[13.6]	[26.3]	[27.3]	[76.2]	[22.7]	[45.5]
Robust QLR	0	2	4	5	1	3
	[0.0]	[10.5]	[18.2]	[23.8]	[4.5]	[27.3]
MW	1	4	4	11	1	6
	[4.5]	[21.1]	[18.2]	[52.4]	[4.5]	[54.5]
Robust MW	1	3	4	4	1	3
	[4.5]	[15.8]	[18.2]	[19.0]	[4.5]	[27.3]
APW	3	5	6	17	5	6
	[13.6]	[26.3]	[27.3]	[81.0]	[22.7]	[54.5]
Robust APW	1	3	3	5	2	3
	[4.5]	[15.8]	[13.6]	[23.8]	[9.1]	[27.3]

Note: The table shows the number of rejecting the null hypothesis of parameter stability across different test statistics. The number in bracket is the percentage of rejection. The level of significance is 5%. PK sup is the maximal OLS CUSUM statistic by Ploberger and Kramer (1992). PK msq is the mean square version. Nyblom is the test by Nyblom (1989). QLR is Quandt (1960) likelihood ratio statistic. MW is the mean Wald statisitic by Hansen (1992) and Andrews and Ploberger (1994). APW is the exponential average Wald statistic by Andrew and Ploberger (1994). Robust means the heteroskedascity-robust version. See Smith and Galesi (2014) for details.

Table 9: *F* statistics for testing the weak exogeneity of the country-specific foreign variables and global variables

		cv	ips	ppis	cpiHs	cpiCs	rs	poil	pfood
brazil	F(2,129)	3.07	2.18	0.51	0.15	0.93	0.16	0.16	2.31
canada	F(4,124)	2.44	0.47	0.56	0.48	0.17	1.31	1.59	1.26
chile	F(2,129)	3.07	1.65	0.57	0.03	0.07	0.33	0.84	0.64
china	F(2,132)	3.06	0.86	2.23	1.50	0.09	0.01	2.72	1.41
euro	F(1,127)	3.92	0.25	0.28	0.32	0.22	2.49	0.13	4.82 *
india	F(2,129)	3.07	1.60	0.04	0.23	0.65	1.47	0.48	0.74
indonesia	F(2,129)	3.07	0.39	0.04	0.09	2.06	1.03	0.43	1.04
japan	F(3,125)	2.68	1.92	1.30	0.02	1.00	1.16	3.52 *	1.82
korea	F(4,124)	2.44	0.53	1.22	0.69	0.26	0.35	1.26	1.24
malaysia	F(1,130)	3.91	1.62	0.00	0.27	0.99	4.41 *	0.04	0.50
mexico	F(3,125)	2.68	0.99	0.58	0.04	0.36	1.11	1.26	0.50
norway	F(2,126)	3.07	0.69	0.31	1.23	0.34	0.37	0.04	0.47
peru	F(4,127)	2.44	2.09	1.07	1.56	0.38	0.33	0.27	1.58
philippines	F(2,129)	3.07	1.11	0.44	0.50	1.16	0.97	1.45	1.16
saudi_arabia	F(1,136)	3.91	0.01	0.00	0.73	3.47	0.80	0.49	4.69 *
singapore	F(2,129)	3.07	0.02	2.05	0.50	0.06	1.49	1.69	1.48
south_africa	F(3,128)	2.68	1.57	0.43	0.91	0.31	0.46	1.47	0.94
sweden	F(2,126)	3.07	0.14	1.42	3.92 *	1.38	0.79	0.32	1.17
thailand	F(2,129)	3.07	1.31	2.16	0.93	1.30	0.78	2.03	2.42
turkey	F(3,125)	2.68	0.12	1.82	0.32	1.51	0.69	1.56	1.47
uk	F(0,128)								
usa	F(5,127)	2.29	0.61	0.72	0.66	2.26		0.48	0.49

Note: * denotes that the corresponding statistics are significant at 5%.

Table 10: Average pair-wise cross-section correlations of variables used in the GVAR model and associated model's residuals

	industrial production, ip				producer price index, ppi				heaadline CPI, cpiH			
			VECMX* Res				VECMX* Res				VECMX* Res	
	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2
brazil	0.626	0.109	0.033	−0.020	0.911	0.147	0.069	0.024	0.930	0.036	0.044	0.017
canada	0.712	0.154	0.092	0.026	0.907	0.321	0.135	0.008	0.936	0.184	0.102	0.015
chile	0.690	0.032	0.006	0.008					0.940	0.209	0.112	0.038
china	0.685	0.050	−0.004	0.003					0.937	0.075	−0.013	−0.054
euro	0.284	0.166	0.113	−0.003	0.944	0.468	0.163	−0.017	0.936	0.239	0.089	−0.031
india	0.680	0.080	0.050	0.006	0.922	0.296	0.086	−0.012	0.933	0.007	−0.006	−0.027
indonesia	0.599	0.047	0.025	0.005	0.935	0.288	0.123	0.003	0.933	0.043	0.005	−0.016
japan	0.631	0.045	0.008	−0.027	0.779	0.369	0.087	−0.003	−0.030	0.145	0.057	−0.007
korea	0.698	0.120	0.069	0.016	0.934	0.423	0.162	0.036	0.935	0.159	0.016	−0.008
malaysia	0.706	0.107	0.085	0.014	0.945	0.386	0.119	−0.013	0.934	0.049	−0.001	0.013
mexico	0.719	0.072	0.048	0.025	0.940	0.222	0.103	0.032	0.940	0.035	−0.012	−0.005
norway	−0.686	0.032	0.031	0.013	0.941	0.328	0.094	−0.007	0.937	0.028	0.010	−0.019
peru	0.689	0.074	0.033	0.027	0.940	0.266	0.072	−0.001	0.940	0.113	0.036	0.013
philippines	0.655	0.063	0.058	0.035	0.624	0.197	0.091	0.002	0.938	0.158	0.015	0.001
saudi_arabia	0.541	0.030	0.022	0.001					0.925	0.109	0.007	0.017
singapore	0.684	0.051	0.052	−0.034	0.912	0.391	0.151	−0.014	0.921	0.145	0.055	−0.006
south_africa	0.545	0.082	0.068	0.012	0.925	0.117	0.051	0.001	0.935	0.141	0.054	0.020
sweden	0.450	0.025	0.026	−0.003	0.919	0.278	0.108	0.031	0.919	0.176	0.079	0.018
thailand	0.670	0.052	0.040	−0.014	0.947	0.381	0.102	−0.018	0.934	0.166	0.066	0.015
turkey	0.705	0.072	0.075	0.004	0.910	0.172	0.086	0.030	0.916	0.008	0.022	0.006
uk	−0.255	0.085	0.067	0.001	0.928	0.431	0.150	−0.006	0.936	0.186	0.068	−0.003
usa	0.695	0.114	0.051	−0.017	0.947	0.433	0.168	−0.105	0.933	0.241	0.118	−0.022

	core CPI, cpiC				short-term interest rate, r				nominal effective exchange rate, neer			
			VECMX* Res				VECMX* Res				VECMX* Res	
	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2	Levels	1st Diff	Type-1	Type-2
brazil					0.263	0.050	0.009	−0.005	0.024	0.113	0.087	0.087
canada	0.808	0.045	0.026	0.012	0.552	0.292	0.137	0.034	0.004	0.032	0.011	0.028
chile	0.810	0.087	0.044	0.001	0.386	0.171	−0.025	−0.009	0.052	0.093	0.075	0.050
china					−0.146	0.059	0.023	−0.070	−0.079	−0.009	0.049	0.052
euro	0.804	0.076	0.037	−0.042	0.557	0.343	0.147	0.040	−0.074	−0.195	−0.201	−0.203
india					−0.291	−0.003	0.004	0.028	−0.033	0.115	0.095	0.096
indonesia					0.320	0.040	0.026	0.003	0.002	0.066	0.059	0.063
japan	−0.777	0.033	0.002	−0.011	0.231	0.181	0.067	0.028	−0.023	−0.184	−0.167	−0.175
korea	0.806	0.070	0.023	−0.001	0.554	0.286	0.096	0.050	−0.029	0.042	0.034	0.038
malaysia					0.288	0.217	0.009	−0.035	−0.001	0.114	0.111	0.114
mexico	0.807	0.042	−0.010	−0.007	0.469	0.107	0.004	−0.002	−0.007	0.113	0.102	0.107
norway	0.802	0.073	0.066	−0.011	0.489	0.296	0.103	0.014	0.054	0.013	0.009	0.015
peru					0.332	0.057	0.016	0.028	−0.030	0.018	0.045	0.052
philippines					0.443	0.094	0.017	−0.011	0.001	0.121	0.139	0.144
saudi_arabia									−0.088	0.020	0.066	0.069
singapore					0.387	0.036	0.047	0.015	−0.034	0.033	0.021	0.022
south_africa					0.414	0.137	−0.012	−0.006	−0.015	0.068	0.075	0.057
sweden	0.778	0.074	0.045	−0.050	0.538	0.232	0.047	−0.022	0.011	−0.023	−0.045	−0.046
thailand					0.306	0.227	0.073	0.046	−0.024	0.092	0.092	0.104
turkey	0.787	0.060	0.005	−0.008	0.364	0.099	0.041	0.032	−0.008	0.110	0.081	0.083
uk	0.798	0.027	0.054	−0.012	0.517	0.276	0.175	0.001	−0.056	−0.033	−0.038	−0.032
usa	0.809	0.042	0.028	−0.019	0.484	0.244	0.157	0.047	−0.098	−0.031	0.012	0.023

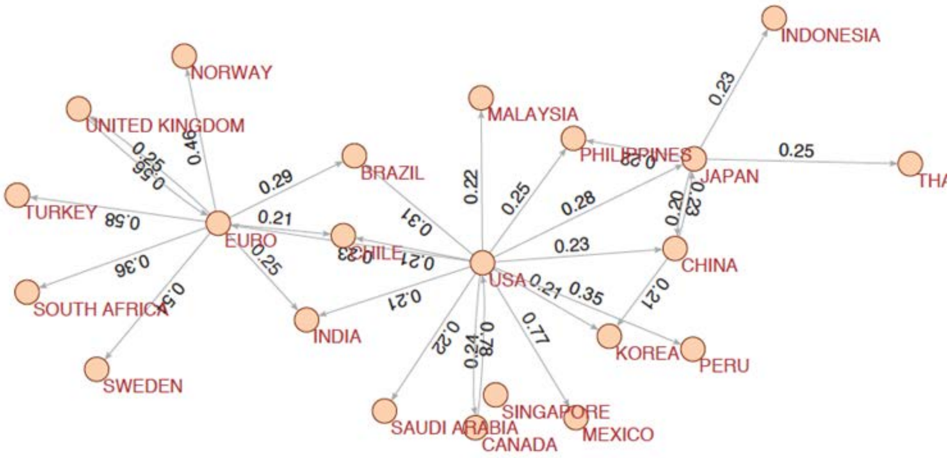
Note: VARX* Res (Type-2) refers to residuals from country-specific VARX* models. The specification is given as Equation (2). VARX* Res (Type-1) are obtained after re-estimating the model without the contemporaneous "star" variables.

Table 11: Instantaneous effects of foreign variables on domestic counterparts by countries

	ip		ppi		cpiH		cpiC		r	
brazil	0.729	**	0.158		0.214				0.185	
canada	0.274	***	0.308	***	1.096	***	0.121		0.373	***
chile	0.253				0.489	**	0.736	**	−0.080	
china	0.026				0.937	***			0.370	
euro	0.506	***	0.346	***	0.192	**	0.117	**	0.322	***
india	0.554	***	0.128		−0.105				−0.441	
indonesia	0.285		0.723	**	−0.582				0.236	**
japan	0.050		0.119	*	0.113		0.037		0.017	
korea	0.800	***	0.553	***	−0.154		0.128		0.128	**
malaysia	0.420	***	0.669	***	−0.103				0.008	
mexico	0.222	*	0.104	*	−0.215		−0.014		−0.068	
norway	−0.082		0.925		0.627	**	1.474	***	0.667	***
peru	0.353		0.065		0.357	*			−0.226	
philippines	−0.036		0.693	**	0.066				0.145	
saudi_arabia	−0.029				−0.174					
singapore	1.652	***	1.444	***	0.740	***			0.305	
south_africa	0.672	***	1.207		0.649	**			0.158	
sweden	0.851	***	0.443	***	0.758	***	1.563	***	0.427	**
thailand	0.314		1.241	***	−0.060				0.194	
turkey	1.916	***	0.675	**	0.206		0.441		0.760	
uk	0.363	***	0.215	***	0.318		0.430	*	1.161	***
usa	0.193	**	1.032	***	0.700	***	0.039			

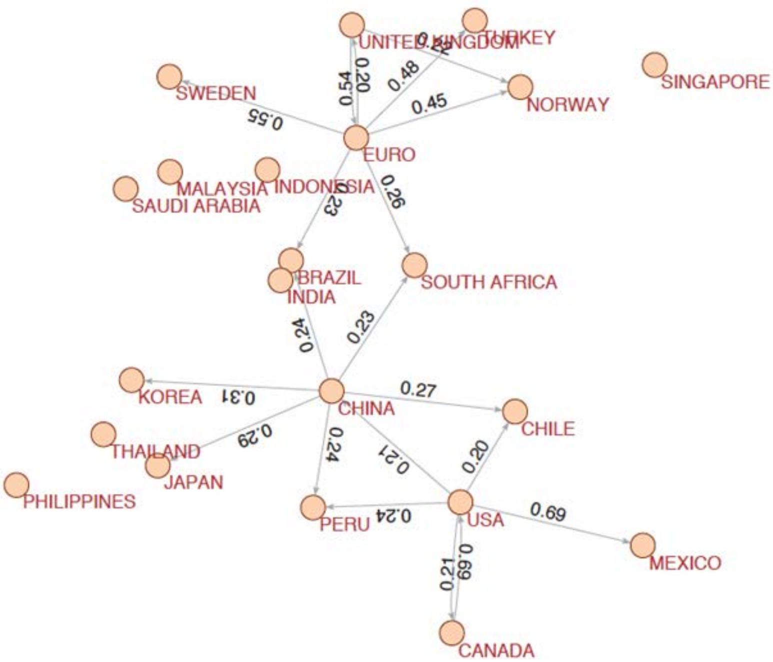
Note: White’s heteroskedasticity robust standard error is used. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Figure 1: Trade links among the sample countries between 2001–2005



Note: IMF Direction of Trade Statistics; Authors' calculation. This graph is drawn by Pajek (Mrvar and Batagelj, 2016). Technically, each country has 21 connecting arrows. In order to simplify the presentation, the arrows are drawn if the trade weights are more than 20%.

Figure 2: Trade links among the sample countries between 2011–2015



Note: IMF Direction of Trade Statistics; Authors' calculation. This graph is drawn by Pajek (Mrvar and Batagelj, 2016). Technically, each country has 21 connecting arrows. In order to simplify the presentation, the arrows are drawn if the trade weights are more than 20%.

Figure 3: Persistence profiles with average trade weights for 2011–2015

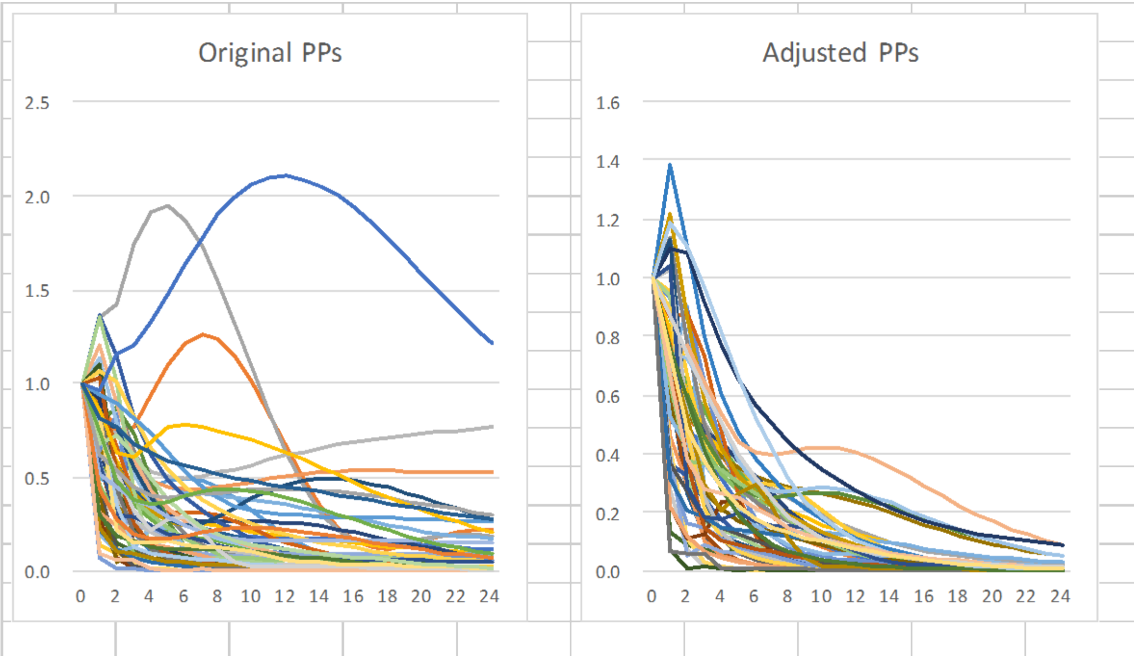
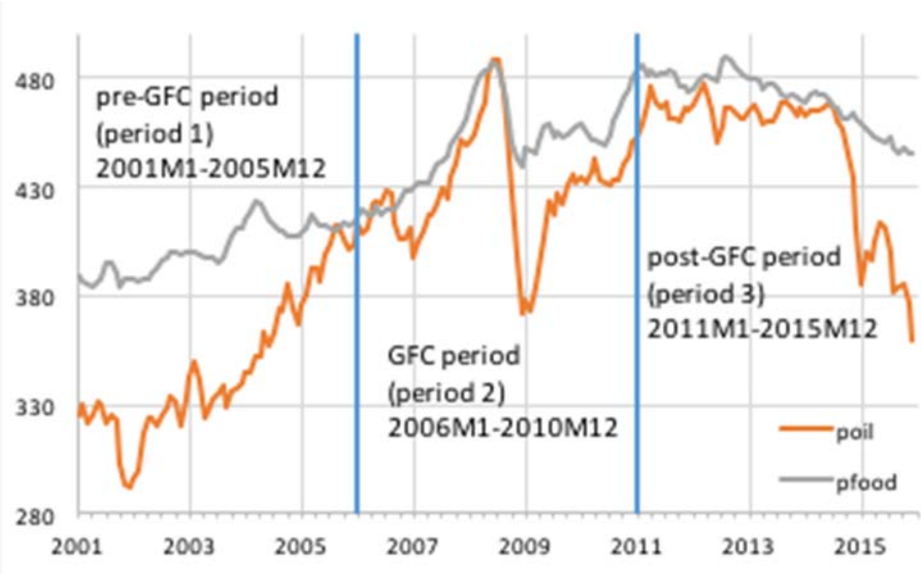
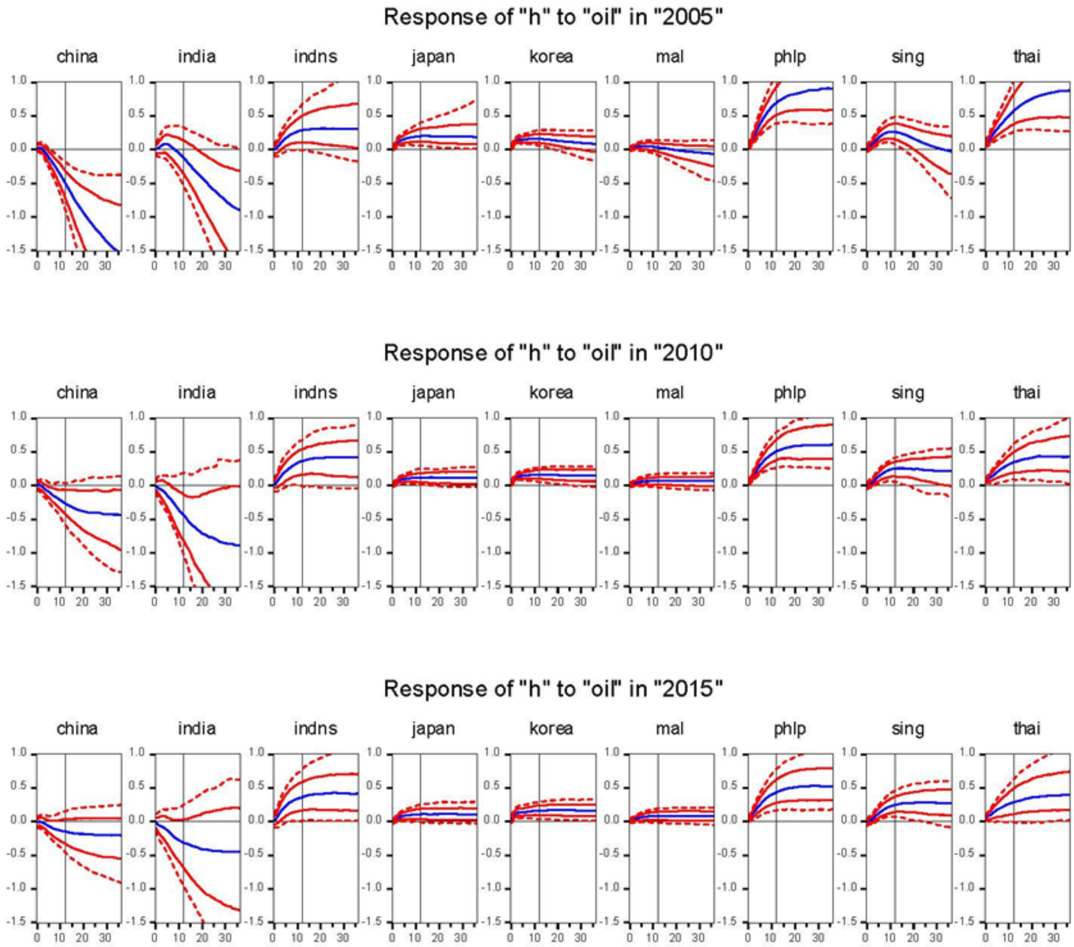


Figure 4: Commodity price indices



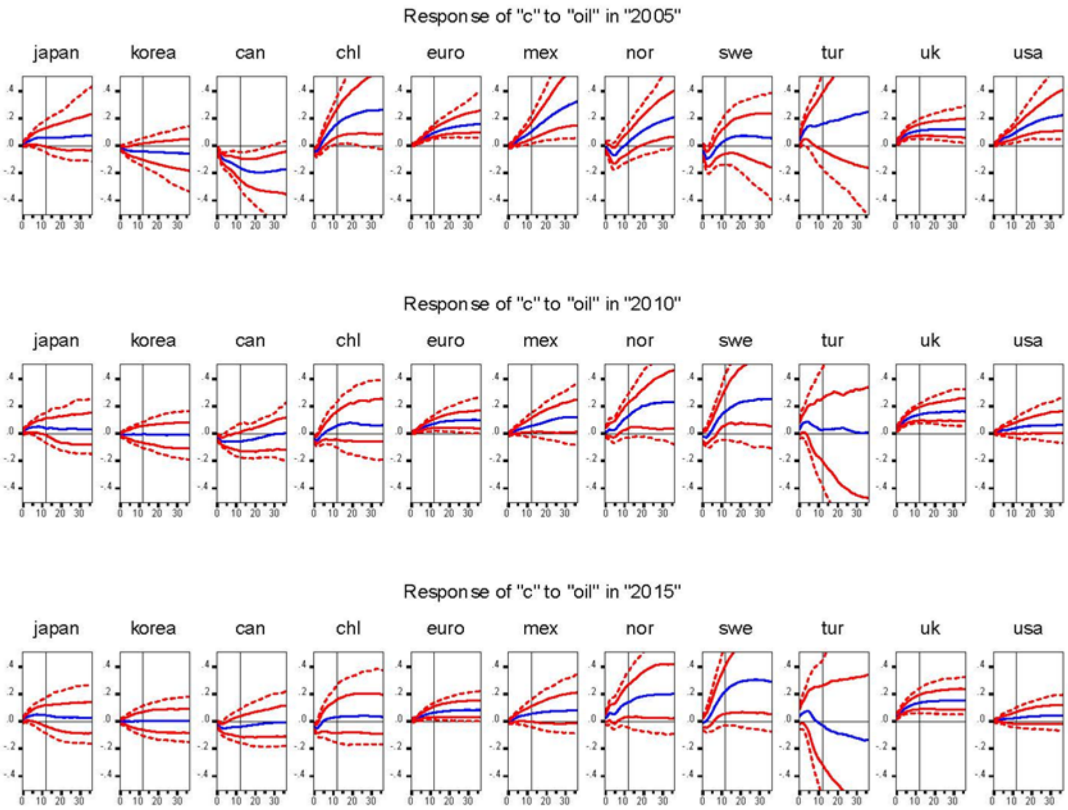
Note: Later in this paper, we investigate the differences of impulse response patterns of the three price indices and the industrial production index to both oil and food price shocks across these three sub-periods.

Figure 5: Responses of p^H to one S.D. increase in p^O



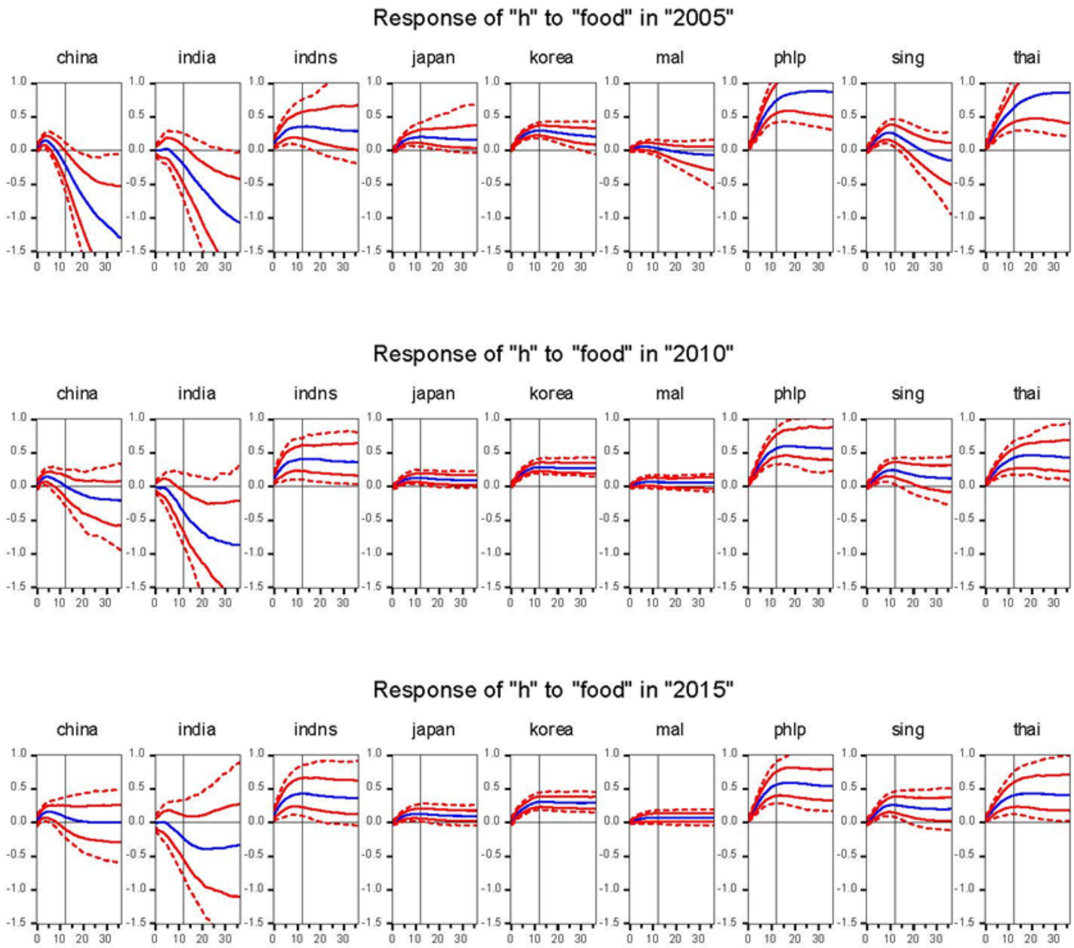
Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16^{th} and 84^{th} percentiles (red line), and 5^{th} and 95^{th} percentiles (red dash). The horizontal axis depicts the months after the shock and the vertical line corresponds to 12 months after the shock.

Figure 6: Responses of p^C to one S.D. increase in p^O



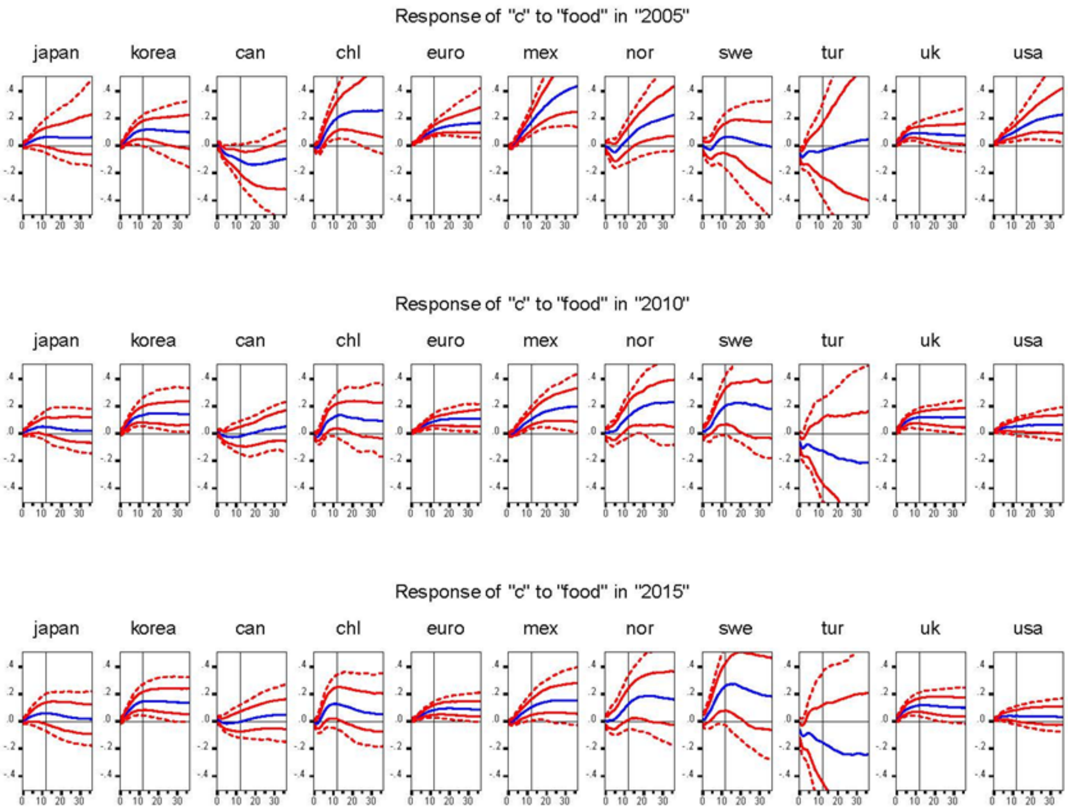
Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16th and 84th percentiles (red line), and 5th and 95th percentiles (red dash).

Figure 7: Responses of p^H to one S.D. increase in food price



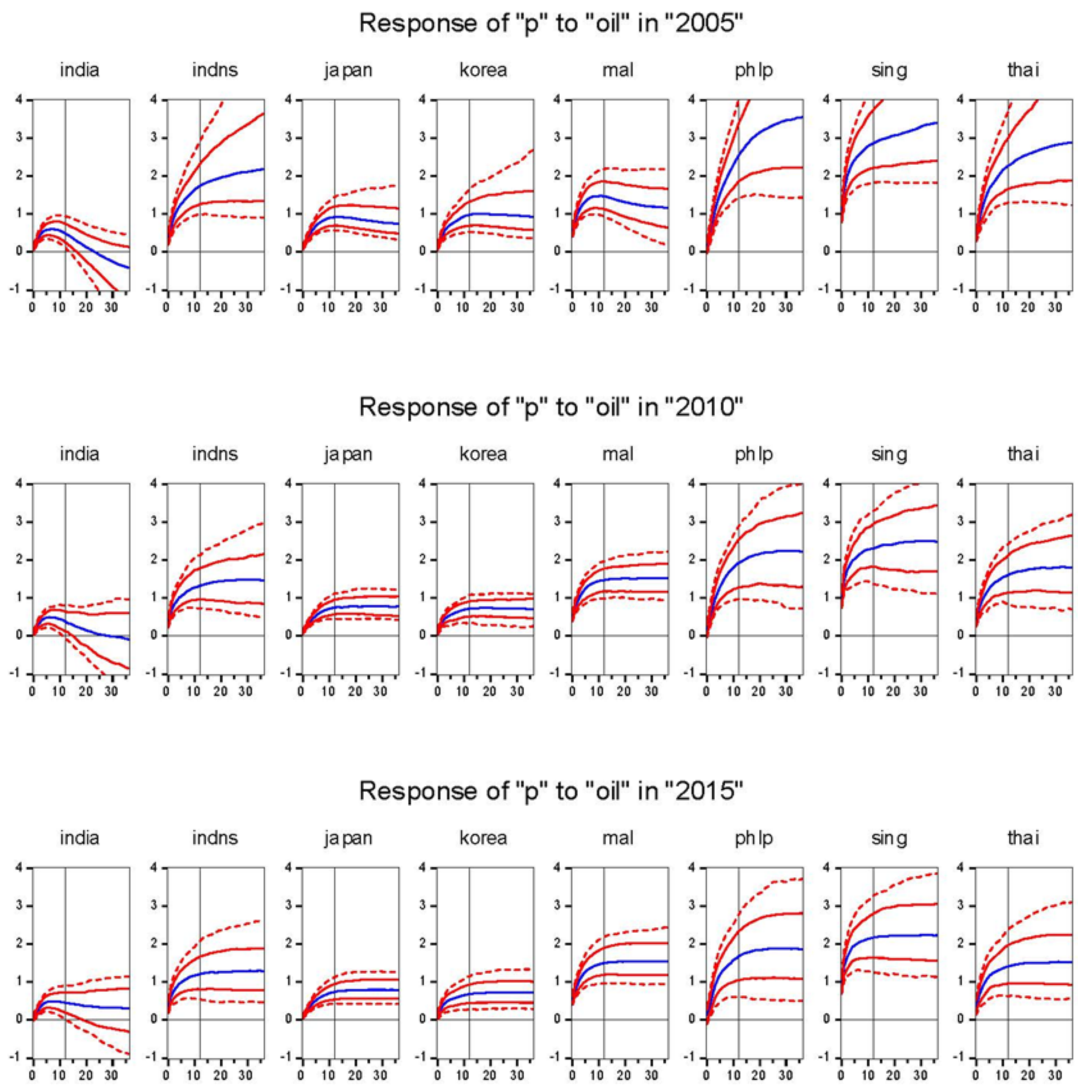
Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16th and 84th percentiles (red line), and 5th and 95th percentiles (red dash).

Figure 8: Responses of p^C to one S.D. increase in food price



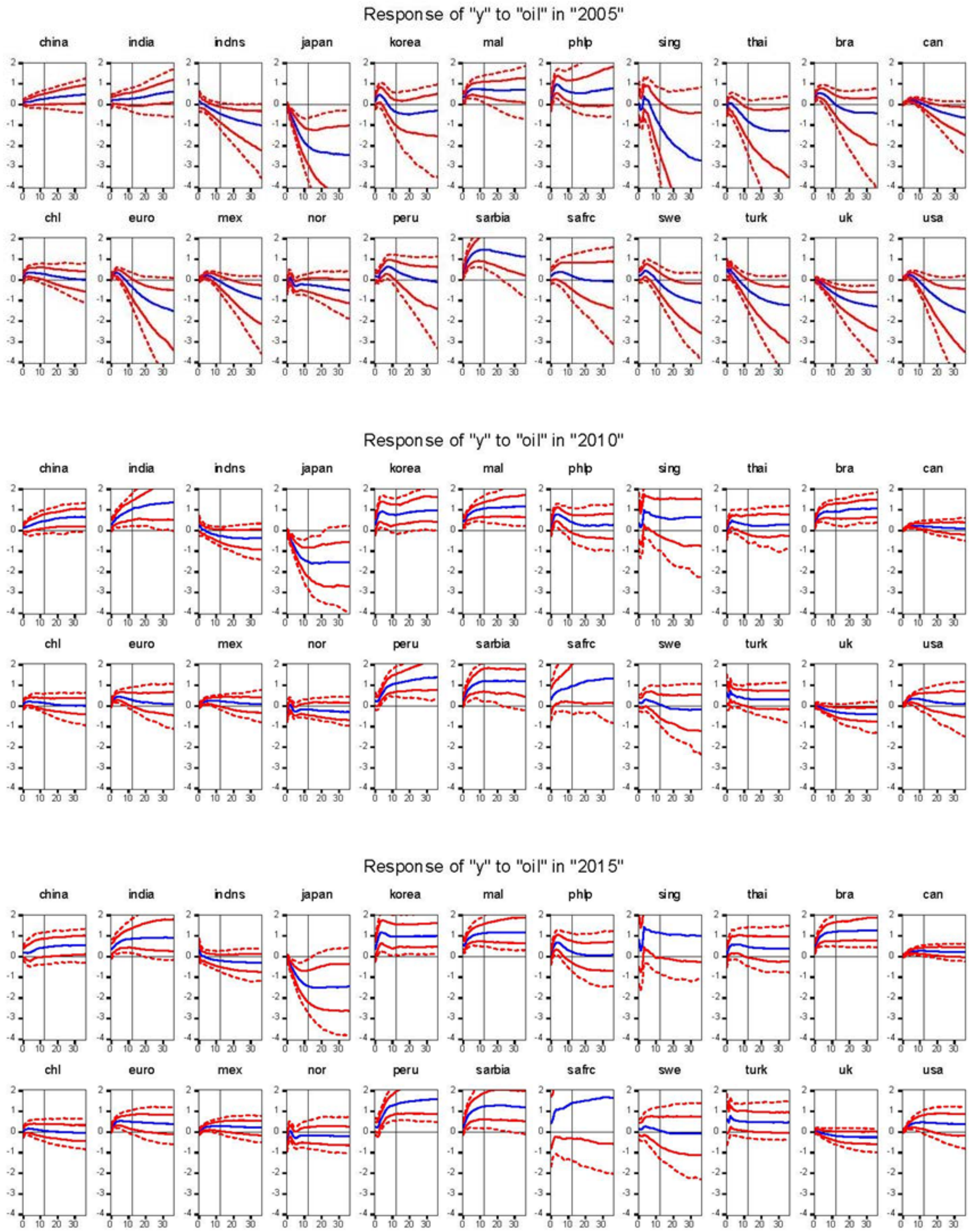
Note: Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16th and 84th percentiles (red line), and 5th and 95th percentiles (red dash).

Figure 9: Responses of P^P to one S.D. increase in p^O



Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16th and 84th percentiles (red line), and 5th and 95th percentiles (red dash).

Figure 10: Responses of y to one S.D. increase in p^O



Note: Please refer to Table 1 for a glossary of acronyms. The lines correspond to the paths of median (blue), 16th and 84th percentiles (red line), and 5th and 95th percentiles (red dash). Asian countries are listed first (in alphabetical order), followed by non-Asian countries (also in alphabetical order).