China's Slowdown and Global Financial Market Volatility: Is World Growth Losing Out?*

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February 25, 2017

Abstract

China's GDP growth slowdown and a surge in global financial market volatility could both adversely affect an already weak global economic recovery. To quantify the global macroeconomic consequences of these shocks, we employ a GVAR model estimated for 26 countries/regions over the period 1981Q1 to 2013Q1. Our results indicate that (i) a one percent permanent negative GDP shock in China (equivalent to a one-off one percent growth shock) could have significant global macroeconomic repercussions, with world growth reducing by 0.23 percentage points in the short-run; and (ii) a surge in global financial market volatility could translate into a fall in world economic growth of around 0.29 percentage points, but it could also have negative short-run impacts on global equity markets, oil prices and long-term interest rates.

JEL Classifications: C32, E32, F44, O53.

Keywords: China's slowdown, global financial market volatility, international business cycle, and Global VAR.

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*We are grateful to Patrick Blagrave, Mai Dao, Luc Everaert, Jaime Guajardo, Emmanouil Kitsios, Vladimir Klyuev, Ruy Lama, Malhar Nabar, Jin Zhongxia and seminar participants at the IMF for helpful comments and suggestions. We would also like to thank the editor in charge of our paper and two anonymous referees for helpful suggestions. The views expressed in this paper are those of the authors and do not necessarily represent those of the International Monetary Fund or IMF policy.

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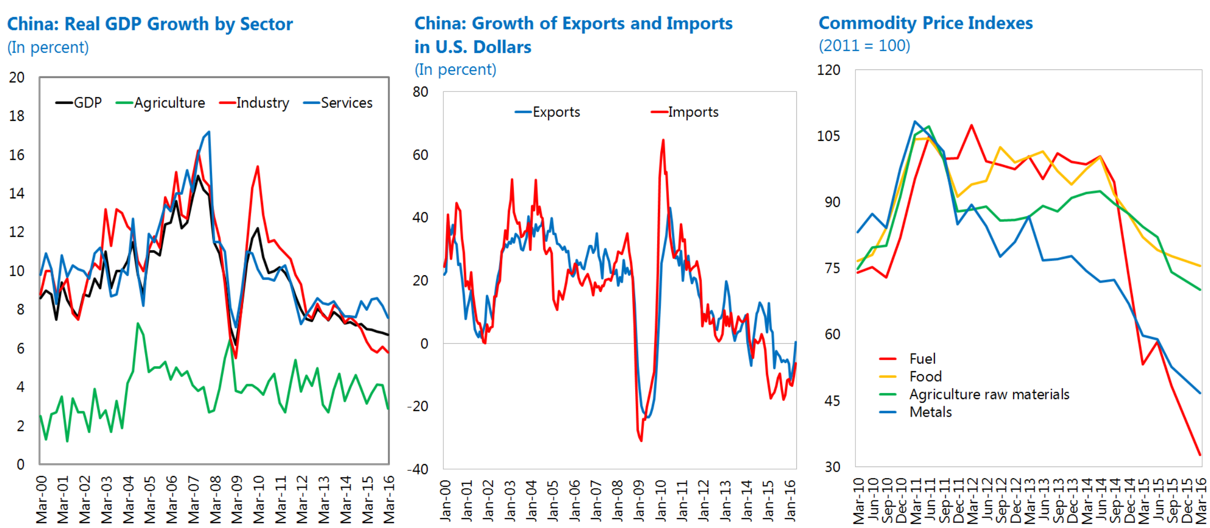
1 Introduction

China's real GDP growth is slowing—from an average of about 10 percent over the period 1980–2013 to 7 percent between 2014 and 2016. The value of China's imports has also been contracting significantly since late 2014, weighing on economic growth in those exporting countries that cater to China's final demand (including Asian countries). This growth slowdown is largely driven by China's gradual "rebalancing" from exports to domestic demand, from manufacturing to services, and from investment to consumption (Figure 1).[1] These developments, together with market concerns about the future performance of the Chinese economy, are resulting in spillovers to other economies (especially to countries in the Asia and Pacific region) through trade links, weaker commodity prices, and financial linkages.

Figure 1: China's Real GDP Growth and Rebalancing



Source: Dizioli et al. (2016).

Given the emergence of China as a global force in the world economy in recent decades, any slowdown and change in the composition of its GDP growth can bring about significant spillovers to other systemic economies, and its trading partners, including those in the Asia and Pacific region, as well as emerging market commodity exporters. This paper investigates how shocks to GDP in China are transmitted internationally, conditional on alternative configurations of cross-country linkages in the global economy.[2] It also studies how changes

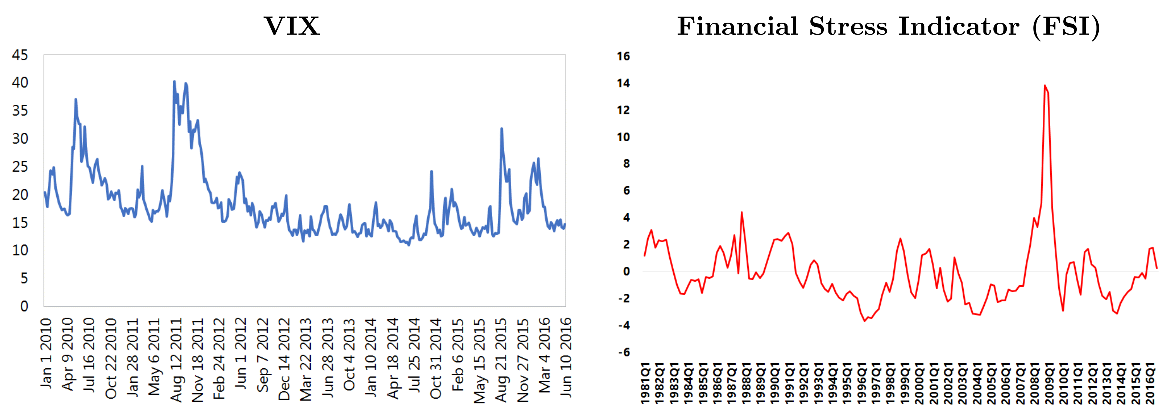
[1] See International Monetary Fund (2015) for details.

[2] While this paper focuses on negative spillovers from a GDP growth shock in China, it should be noted that the stimulus-induced growth in China after the global financial crisis significantly benefited the global economy during its recovery phase.

in China's bilateral trade pattern, including that of trade in value added, may have affected the transmission of China's business cycles to other Asian countries over time.

Furthermore, if China's transition to the new growth model coincides with materialization of domestic financial sector risks, it has the potential to create even larger global spillovers. To account for such possibilities, we also separately examine the international spillover effects of surges in global financial market volatility and their dependence on the depth of financial linkages between countries (i.e., the size of their external balance sheets), in addition to trade and commodity price linkages. We note that excessive global financial market volatility could emanate from disorderly macro-financial developments in China[3] and/or if advanced countries' monetary policy tightening occurs at an accelerated pace, among other reasons (e.g. geopolitical tensions or sharp oil price fluctuations). This additional analysis is particularly important as indicated by the summer 2015 and January 2016 episodes of heightened global financial market volatility (Figure 2). The VIX spiked in August 2015, when China's stock market prices fell sharply despite official support, and the renminbi fixing mechanism was adjusted, leading to renminbi depreciation vis-à-vis the U.S. dollar. Another flare-up occurred in January 2016 coinciding with another large price decline in China's stock market.

Figure 2: Market Volatility Indices



Source: Chicago Board Options Exchange, Cardarelli et al. (2009), and authors' calculations.

To investigate and quantify the global macroeconomic implications of China's slowdown, as well as the consequences of a surge in global financial market volatility, we employ a dynamic multi-country framework, first advanced by Pesaran et al. (2004), known as the Global VAR (GVAR). This compact model of the world economy enables one to analyze the international macroeconomic transmission of shocks (including that of China's growth slow-

[3] Dizioli et al. (2016) argue that China's transition to a new growth model has already coincided with bouts of global financial volatility as the market reassessed the underlying strength of the Chinese economy.

down), taking into account not only the direct exposure of countries to shocks but also the indirect effects through secondary or tertiary channels. The framework comprises 26 region-specific VARX* models (including a single Euro Area region comprising 8 of the 11 countries that adopted the euro in 1999). These individual (VARX*) models are solved in a global setting where core macroeconomic variables of each economy are related to corresponding foreign variables (constructed exclusively to capture each country's bilateral exposures to the other countries through trade and financial linkages). The model has both real and financial variables: real GDP, inflation, the real equity price, the real exchange rate, short and long-term interest rates, and the price of oil. Furthermore, we add an index of financial stress (FSI) as an observable common factor to the GVAR to analyze spillovers from surges in global financial market volatility, including from macro-financial developments in China.

Estimating the GVAR model over the period 1981Q1 to 2013Q1, we illustrate that a negative GDP shock in China could have significant global macroeconomic repercussions through trade links, weaker commodity prices, and financial linkages, especially for less-diversified commodity exporters and ASEAN-5 countries (except for the Philippines).[4] The effects on other Asia-Pacific countries and systemic economies are smaller but not trivial. Overall, our results suggest that following a one percent permanent negative Chinese GDP shock (equivalent to a one-off one percent real GDP growth shock), global growth reduces by 0.23 percentage points in the short-run and oil prices fall by around 2.8% in the long run. There is also evidence for a fall in both global inflation and short-term interest rates, and while the median effect on global equity prices is negative, it is not statistically significant.

Table 1: Trade Shares with China

	1982	1987	1992	1997	2002	2007	2012
Australia	3	3	4	6	10	17	28
Euro Area	1	2	3	5	7	13	15
India	1	1	1	3	7	14	15
Indonesia	1	3	4	5	7	11	16
Japan	4	5	6	10	17	23	26
Korea	0	0	5	11	17	26	28
Malaysia	2	2	2	3	8	13	17
New Zealand	2	2	3	4	7	11	19
Philippines	3	3	1	2	4	11	14
Singapore	3	4	3	4	8	14	14
Thailand	4	4	3	4	8	14	18
UK	0	1	1	1	3	6	8
USA	1	2	4	6	10	16	18

Notes: Computed as the shares of exports and imports of goods of country i with China.
Source: International Monetary Fund's *Direction of Trade Statistics*. Author's estimations.

[4] ASEAN-5 countries include: Indonesia, Malaysia, the Philippines, Singapore and Thailand.

The emergence of China as a key driver of the global economy over recent decades is illustrated in Table 1. While trade with the neighboring countries in the Asia and Pacific region as well as the systemic economics (Euro Area, the U.K., and the U.S.), was very small in the 1980s, we notice that bilateral trade with these countries have increased many fold over time. To give a concrete example, Chinese trade with these countries did not exceeded 4% in 1982, while it was between 8% (the U.K.) and 28% (Australia and Korea) in 2012, with trade shares having increased between 4 (Singapore) and 23 fold (Indonesia and the U.K.) over the last three decades. To investigate the extent to which the global impact of a Chinese negative output shock has changed over the past three decades, we set up and estimate a GVAR model in which the country-specific foreign variables are constructed with time-varying trade weights, while the GVAR is solved with time-specific counterfactual trade weights between 1982 and 2012 (see Cesa-Bianchi et al. (2012) for methodological details). Perhaps not surprisingly, our results show that the responses based on the weights in the 1980s (and in most cases in the 1990s) are not statistically significant for either the systemic economies or the Asia-Pacific region. Nonetheless, they are highly significant and generally larger based on the 2000s weights, thereby reflecting the direction of evolving trade patterns, and China's growing role in the global economy and world commodity markets (Table 1).

Finally, our results indicate that in response to a surge in global financial market volatility, global economic growth decelerates in the short-run. More specifically, a one standard deviation shock to the financial stress index[5] translates into slower global economic activity—with world output falling by around 0.29% below the pre-shock level on average over the first year. We also observe negative short-run effects on global equity prices (−3.7%), oil prices (−6.5%), and long-term interest rates (−0.03%), with the numbers in the brackets corresponding to the peak effects in the first quarter after the shock.

Given the emergence of China as a key contributor to global growth in recent decades, it is not surprising that the analysis of spillovers from a slowdown in China's GDP growth has attracted considerable attention over the last few years, with the analytical coverage of its implications for the global economy intensifying during the second half of 2015. However, most of the recent analyses is qualitative/descriptive, mainly written as reports by international organizations, investment banks, and consultants (see, for instance, International Monetary Fund (2015) and IMF Asia and Pacific Department *Regional Economic Outlooks* in 2014 and 2015), or as opinion pieces by prominent economists such as Mohamed El-Erian (writing in the Financial Times on January 7, 2015) and Paul Krugman (writing in the New

[5] This index measures price movements relative to trend, with a historical average value of zero (implying neutral financial market conditions). The magnitude of the shock is comparable to the 2002 episode of market volatility in advanced economies and is much smaller than the Global Financial Crisis shock.

York Times on January 8, 2015). In recent years, there have also been some papers applying various econometric and/or theoretical models (VARs, Factor Augmented VARs, OLG and DSGE models, and event studies) to investigate the impact of a slowdown in China's growth (i) on its trading partners, see, for instance, Ahuja and Nabar (2012) and Duval et al. (2014); (ii) on particular regions, such as Anderson et al. (2015); or (iii) arising from particular sectors, see Ahuja and Myrvoda (2012). However, most of these analyses have been done without adequate account of potential feedback effects, or by ignoring the indirect exposure of countries to the shocks (through secondary or tertiary channels, such as third-country trade, financial, and commodity markets). We contribute to this literature by employing the GVAR methodology, taking into account: both the temporal and cross-sectional dimensions of the data; real and financial drivers of economic activity; interlinkages and spillovers that exist between different regions; and the effects of unobserved or observed common factors (e.g. financial stress indices and oil prices). This is crucial as the impact of shocks (e.g. China slowdown or financial market volatility) cannot be reduced to one country or region but rather involve multiple regions, and may be amplified or dampened depending on the degree of openness of the countries and their trade and financial structures.

Most closely related to our paper is Cesa-Bianchi et al. (2012), who investigate the impact of China's emergence in the world economy on Latin American countries' business cycles. Our paper differs from theirs in many dimensions. First, we concentrate on the impact of Chinese GDP slowdown on Asian countries in particular, and systemic economies and global growth in general. Second, our modelling approach is different than theirs. For instance, oil in our model is determined in international markets, thereby allowing for both demand and supply conditions to influence the price of oil directly rather than having oil prices being endogenous in the United States model (as is done in Cesa-Bianchi et al. (2012)). The main justification for their approach is that the U.S. is the world's largest oil consumer and a demand-side driver of the price of oil. However, it seems more appropriate for oil prices to be determined in global commodity markets rather in the U.S. model alone, given that oil prices are also affected by, for instance, any disruptions to oil supply in the Middle East (which our modelling approach takes into account). Third, we not only investigate the extent to which the global impact of a China's slowdown (and global financial market volatility) has changed over the past three decades, but we also consider a number of different weighting schemes. More specifically, we show that the results are similar when considering alternative configurations of cross-country linkages in the global economy: trade weights, trade in value added weights, financial weights, as well as mixed weights (both trade and financial weights). Fourth, we extended the sample from 2009Q4 to 2013Q1 thereby including the Great Recession and the start of the recovery from it, and more importantly including the period in which global trade has grown less than world's GDP for the first time in decades (post global financial crisis). Last but not least, we examine the implications of a surge in global financial market volatility (as measured by an increase in the Financial Stress Indicator, FSI) in terms of its effect on individual countries' GDP as well as the global economy in general (GDP, equity prices, and commodity markets to name but a few). Note that including a measure of FSI improves the fit of the model significantly, as FSI captures the effect of global financial cycle (mostly overlooked in the literature).

The rest of the paper is organized as follows. Section 2 describes the GVAR methodology and outlines our modelling approach. Section 3 investigates the macroeconomic effects of the China slowdown while Section 4 examines the implications of global financial market volatility shocks. Finally, Section 5 concludes and offers some policy recommendations.

2 Modelling the Global Economy

Before describing the data and our model specification, we provide a short exposition of the GVAR methodology below.

2.1 The Global VAR (GVAR) Methodology

The Global VAR methodology consists of two main steps. First, each country is modeled individually as a small open economy (except for the United States) by estimating country-specific vector error correction models in which domestic variables are related to both country-specific foreign variables and global variables that are common across all countries (such as oil prices and FSI). Second, a global model is constructed combining all the estimated country-specific models and linking them with a matrix of predetermined cross-country linkages. More specifically, we consider $N+1$ countries in the global economy, indexed by $i = 0, 1, ..., N$. With the exception of the United States, which we label as 0 and take to be the reference country; all other N countries are modelled as small open economies. This set of individual VARX* models is used to build the GVAR framework. Following Pesaran et al. (2004) and Dees et al. (2007), a VARX* (p_i, q_i) model for the ith country relates a $k_i \times 1$ vector of domestic macroeconomic variables (treated as endogenous), $\mathbf{x}_{it}$, to a $k_i^* \times 1$ vector of country-specific foreign variables (taken to be weakly exogenous), $\mathbf{x}_{it}^*$:

$$\mathbf{\Phi}_i \left(L, p_i\right) \mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1} t + \mathbf{\Lambda}_i \left(L, q_i\right) \mathbf{x}_{it}^* + \mathbf{u}_{it}, \tag{1}$$

for $t = 1, 2, ..., T$, where $\mathbf{a}_{i0}$ and $\mathbf{a}_{i1}$ are $k_i \times 1$ vectors of fixed intercepts and coefficients on the deterministic time trends, respectively, and $\mathbf{u}_{it}$ is a $k_i \times 1$ vector of country-specific shocks, which we assume are serially uncorrelated with zero mean and a non-singular covariance matrix, $\mathbf{\Sigma}_{ii}$, namely $\mathbf{u}_{it} \sim i.i.d.\left(0, \mathbf{\Sigma}_{ii}\right)$. For algebraic simplicity, we abstract from observed global factors in the country-specific VARX* models. Furthermore, $\mathbf{\Phi}_i\left(L, p_i\right) = I - \sum_{i=1}^{p_i} \mathbf{\Phi}_i L^i$ and $\mathbf{\Lambda}_i\left(L, q_i\right) = \sum_{i=0}^{q_i} \mathbf{\Lambda}_i L^i$ are the matrix lag polynomial of the coefficients associated with the domestic and foreign variables, respectively. As the lag orders for these variables, p_i and q_i, are selected on a country-by-country basis, we are explicitly allowing for $\mathbf{\Phi}_i\left(L, p_i\right)$ and $\mathbf{\Lambda}_i\left(L, q_i\right)$ to differ across countries.

The country-specific foreign variables are constructed as cross-sectional averages of the domestic variables using data on, for instance, bilateral trade as the weights, w_{ij}:

$$\mathbf{x}_{it}^{*} = \sum_{j=0}^{N} w_{ij} \mathbf{x}_{jt}, \tag{2}$$

where $j = 0, 1, ...N$, $w_{ii} = 0$, and $\sum_{j=0}^{N} w_{ij} = 1$. For empirical application, we estimate the model using various weights (see Section 3), thereby illustrating the robustness of our results to the choice of w_{ij}.

Although estimation is done on a country-by-country basis, the GVAR model is solved for the world as a whole, taking account of the fact that all variables are endogenous to the system as a whole. After estimating each country VARX*(p_i, q_i) model separately, all the $k = \sum_{i=0}^{N} k_i$ endogenous variables, collected in the $k \times 1$ vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$, need to be solved simultaneously using the link matrix defined in terms of the country-specific weights. To see this, we can write the VARX* model in equation (1) more compactly as:

$$\mathbf{A}_i\left(L, p_i, q_i\right) \mathbf{z}_{it} = \boldsymbol{\varphi}_{it}, \tag{3}$$

for $i = 0, 1, ..., N$, where

$$\begin{aligned} \mathbf{A}_i\left(L, p_i, q_i\right) &= \left[\mathbf{\Phi}_i\left(L, p_i\right) - \mathbf{\Lambda}_i\left(L, q_i\right)\right], \quad \mathbf{z}_{it} = \left(\mathbf{x}'_{it}, \mathbf{x}'^{*}_{it}\right)', \\ \boldsymbol{\varphi}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1} t + \mathbf{u}_{it}. \end{aligned} \tag{4}$$

Note that given equation (2) we can write:

$$\mathbf{z}_{it} = \mathbf{W}_i \mathbf{x}_t, \tag{5}$$

where $\mathbf{W}_i = \left(\mathbf{W}_{i0}, \mathbf{W}_{i1}, ..., \mathbf{W}_{iN}\right)$, with $\mathbf{W}_{ii} = 0$, is the $(k_i + k_i^{*}) \times k$ weight matrix for country i defined by the country-specific weights, w_{ij}. Using (5) we can write (3) as:

$$\mathbf{A}_i\left(L, p\right)\mathbf{W}_i\mathbf{x}_t = \varphi_{it}, \tag{6}$$

where $\mathbf{A}_i\left(L, p\right)$ is constructed from $\mathbf{A}_i\left(L, p_i, q_i\right)$ by setting $p = \max\left(p_0, p_1, ..., p_N, q_0, q_1, ..., q_N\right)$ and augmenting the $p-p_i$ or $p-q_i$ additional terms in the power of the lag operator by zeros. Stacking equation (6), we obtain the Global VAR(p) model in domestic variables only:

$$\mathbf{G}\left(L, p\right)\mathbf{x}_t = \varphi_t, \tag{7}$$

where

$$\mathbf{G}\left(L, p\right) = \begin{pmatrix} \mathbf{A}_0\left(L, p\right)\mathbf{W}_0 \\ \mathbf{A}_1\left(L, p\right)\mathbf{W}_1 \\ . \\ . \\ . \\ \mathbf{A}_N\left(L, p\right)\mathbf{W}_N \end{pmatrix}, \quad \varphi_t = \begin{pmatrix} \varphi_{0t} \\ \varphi_{1t} \\ . \\ . \\ . \\ \varphi_{Nt} \end{pmatrix}. \tag{8}$$

For an early illustration of the solution of the GVAR model, using a VARX*$(1, 1)$ model, see Pesaran et al. (2004), and for an extensive survey of the latest developments in GVAR modeling, both the theoretical foundations of the approach and its numerous empirical applications, see Chudik and Pesaran (2016). The GVAR(p) model in equation (7) can be solved recursively and used for a number of purposes, such as forecasting or impulse response analysis.

Chudik and Pesaran (2013) extend the GVAR methodology to a case in which common variables are added to the conditional country models (either as observed global factors or as dominant variables). In such circumstances, equation (1) should be augmented by a vector of dominant variables, $\boldsymbol{\omega}_t$, and its lag values:

$$\boldsymbol{\Phi}_i\left(L, p_i\right)\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \boldsymbol{\Lambda}_i\left(L, q_i\right)\mathbf{x}^*_{it} + \boldsymbol{\Upsilon}_i\left(L, s_i\right)\boldsymbol{\omega}_t + \mathbf{u}_{it}, \tag{9}$$

where $\boldsymbol{\Upsilon}_i\left(L, s_i\right) = \sum_{i=0}^{s_i}\boldsymbol{\Upsilon}_i L^i$ is the matrix lag polynomial of the coefficients associated with the common variables. Here, $\boldsymbol{\omega}_t$ can be treated (and tested) as weakly exogenous for the purpose of estimation. The marginal model for the dominant variables can be estimated with or without feedback effects from $\mathbf{x}_t$. To allow for feedback effects from the variables in the GVAR model to the dominant variables via cross-section averages, we define the following model for $\boldsymbol{\omega}_t$:

$$\boldsymbol{\omega}_t = \sum_{l=1}^{p_w} \boldsymbol{\Phi}_{\omega l} \boldsymbol{\omega}_{i,t-l} + \sum_{l=1}^{p_w} \boldsymbol{\Lambda}_{\omega l} \mathbf{x}^*_{i,t-l} + \boldsymbol{\eta}_{\omega t} \tag{10}$$

It should be noted that contemporaneous values of star variables (* superscript) do not feature in equation (10) and $\boldsymbol{\omega}_t$ are "causal". Conditional (9) and marginal models (10) can be combined and solved as a complete GVAR model as explained earlier.

2.2 Model Specification

Our model includes 33 economies, which together cover more than 90% of world GDP, see Table 2. For empirical application, we create a euro area block comprising 8 of the 11 countries that initially joined the Euro in 1999: Austria, Belgium, Finland, France, Germany, Italy, Netherlands, and Spain. The time series data for the euro area are constructed as cross-sectionally weighted averages of the domestic variables, using Purchasing Power Parity GDP weights, averaged over the 2009-2011 period. Thus, as displayed in Table 2, the GVAR model that we specify includes 26 country/region-specific VARX* models.

Table 2: Countries and Regions in the GVAR Model

Asia and Pacific	**North America**	**Europe**
Australia	Canada	Austria*
China	Mexico	Belgium*
India	United States	Finland*
Indonesia		France*
Japan	**South America**	Germany*
Korea	Argentina	Italy*
Malaysia	Brazil	Netherlands*
New Zealand	Chile	Norway
Philippines	Peru	Spain*
Singapore		Sweden
Thailand	**Middle East and Africa**	Switzerland
	Saudi Arabia	Turkey
	South Africa	United Kingdom

Notes: * indicates that the country is included in the euro area block.

We specify two different sets of individual country-specific models. The first model is common across all countries, apart from the United States. These 25 VARX* models include a maximum of six domestic variables (depending on whether data on a particular variable is available), or using the same terminology as in equation (1):

$$\mathbf{x}_{it} = \left[y_{it},\ \pi_{it},\ eq_{it},\ r_{it}^{S},\ r_{it}^{L},\ ep_{it}\right]', \tag{11}$$

where y_{it} is the log of the real Gross Domestic Product at time t for country i, π_{it} is inflation, eq_{it} is the log of real equity prices, r_{it}^{S} (r_{it}^{L}) is the short (long) term interest rate, and ep_{it} is the real exchange rate. In addition, all domestic variables, except for that of the real exchange rate, have corresponding foreign variables computed as in equation (2):

$$\mathbf{x}_{it}^{*} = \left[y_{it}^{*},\ \pi_{it}^{*},\ eq_{it}^{*},\ r_{it}^{*S},\ r_{it}^{*L}\right]'. \tag{12}$$

Following the GVAR literature, the twenty-sixth model (United States) is specified differently, mainly because of the dominance of the United States in the world economy. First, given the importance of U.S. financial variables in the global economy, the U.S.-specific foreign financial variables, $eq_{US,t}^{*}$, $r_{US,t}^{*S}$, and $r_{US,t}^{*L}$, are not included in this model. The appropriateness of exclusion of these variables was also confirmed by statistical tests, in which the weak exogeneity assumption was rejected for $eq_{US,t}^{*}$, $r_{US,t}^{*S}$, and $r_{US,t}^{*L}$. Second, since e_{it} is expressed as the domestic currency price of a United States dollar, it is by construction determined outside this model. Thus, instead of the real exchange rate, we included $e_{US,t}^{*} - p_{US,t}^{*}$ as a weakly exogenous foreign variable in the U.S. model.[6]

Given our interest in analyzing the macroeconomic effects of a surge in global financial market volatility, we need to include an index of financial stress (FSI_t) in advanced economies in our framework. The FSI_t for advanced countries is constructed by Cardarelli et al. (2009) as an average of the following indicators: the "beta" of banking sector stocks; TED spread; the slope of the yield curve; corporate bond spreads; stock market returns; time-varying stock return volatility; and time-varying effective exchange rate volatility. Such an index facilitates the identification of large shifts in asset prices (stock and bond market returns); an abrupt increase in risk/uncertainty (stock and foreign exchange volatility); liquidity tightening (TED spreads); and the health of the banking system (the beta of banking sector stocks and the yield curve). We model FSI_t as a common variable, in other words, it is included as a weakly exogenous variable in each of the 26 country/region-specific VARX* models, but we allow for feedback effects from any of the macro variables to FSI_t. Finally, to capture the influence of China's slowdown on global commodity markets we also include the price of oil (log of the nominal oil prices in U.S. dollars) as a common variable in our model.[7]

[6]Weak exogeneity test results for all countries and variables are available upon request.

[7]See also Cashin et al. (2017) and Mohaddes and Pesaran (2016a, 2016b) for a more detailed description of how the global oil market is incorporated in the GVAR framework.

2.3 Country-Specific Estimates

We obtain data on $\mathbf{x}_{it}$ for the 33 countries included in our sample (see Table 2) as well as oil prices from the GVAR website: https://sites.google.com/site/gvarmodelling, see Smith and Galesi (2014) for more details. As explained earlier the financial stress index (FSI_t) is constructed using the methodology of Cardarelli et al. (2009). We use quarterly observations over the period 1981Q1–2013Q1 to estimate the 26 country-specific VARX*(p_i, q_i) models. However, prior to estimation, we determine the lag orders of the domestic and foreign variables, p_i and q_i. For this purpose, we use the Akaike Information Criterion (AIC) applied to the underlying unrestricted VARX* models. Given data constraints, we set the maximum lag orders to $p_{\max} = 2$ and $q_{\max} = 1$. The selected VARX* orders are reported in Table 3. Moreover, the lag order selected for the univariate FSI_t model is $(2, 1)$ based on the AIC.

Table 3: Lag Orders of the Country-Specific VARX*(p,q) Models Together with the Number of Cointegrating Relations (r)

Country	VARX* Order		Cointegrating relations (r_i)	Country	VARX* Order		Cointegrating relations (r_i)
	p_i	q_i			p_i	q_i	
Argentina	2	1	1	Norway	2	1	3
Australia	2	1	4	New Zealand	2	1	3
Brazil	1	1	1	Peru	2	1	2
Canada	1	1	3	Philippines	2	1	2
China	1	1	2	South Africa	2	1	1
Chile	2	1	3	Saudi Arabia	2	1	1
Euro Area	2	1	2	Singapore	2	1	2
India	2	1	2	Sweden	2	1	3
Indonesia	2	1	3	Switzerland	2	1	2
Japan	1	1	4	Thailand	1	1	2
Korea	1	1	3	Turkey	1	1	3
Malaysia	1	1	2	UK	1	1	3
Mexico	1	1	3	USA	2	1	2

Notes: p_i and q_i denote the lag order for the domestic and foreign variables respectively and are selected by the Akaike Information Criterion (AIC). The number of cointegrating relations (r_i) are selected using the trace test statistics based on the 95% critical values from MacKinnon (1991) for all countries except for Brazil, Canada, India, Japan, Korea, South Africa, Saudi Arabia, and Singapore, for which we reduced r_i below those suggested by the trace statistic to ensure that the persistence profiles were well behaved and the stability of the global model.
Source: Author's estimations.

Having established the lag order of the 26 VARX* models, we proceed to determine the number of long-run relations. Cointegration tests with the null hypothesis of no cointegration, one cointegrating relation, and so on are carried out using Johansen's maximal eigenvalue and trace statistics as developed in Pesaran et al. (2000) for models with weakly exogenous $I(1)$ regressors, unrestricted intercepts and restricted trend coefficients. We choose the number of cointegrating relations (r_i) based on the trace test statistics using the 95% critical values from MacKinnon (1991). We then consider the effects of system-wide shocks on the exactly-identified cointegrating vectors using persistence profiles developed by Lee and Pesaran (1993) and Pesaran and Shin (1996). On impact the persistence profiles (PPs) are normalized to take the value of unity, but the rate at which they tend to zero provides information on the speed with which equilibrium correction takes place in response to shocks. The PPs could initially over-shoot, thus exceeding unity, but must eventually tend to zero if the vector under consideration is indeed cointegrated. In our analysis of the PPs, we noticed that the speed of convergence was very slow for Brazil, Canada, India, Japan, Korea, South Africa, Saudi Arabia, and Singapore, so we reduced r_i by one for each country resulting in well behaved PPs overall. The final selection of the number of cointegrating relations are reported in Table 3.

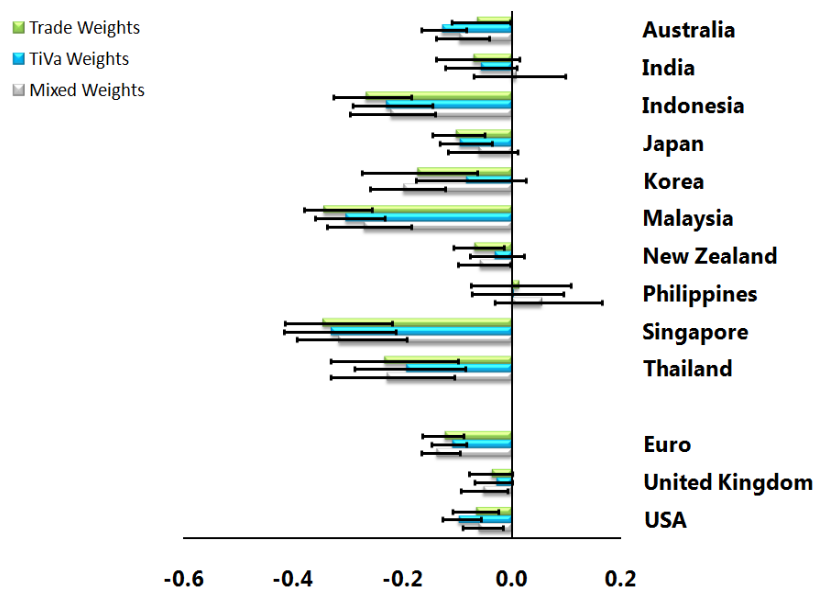
3 The Effects of China's Slowdown

This section illustrates the global macroeconomic effects of China's slowdown, including by reporting the country-specific annual output elasticities following a one percent permanent negative GDP shock in China and the associated 16th and 84th percentile error bands. Figure 3 clearly shows that a Chinese negative output shock has a large (and statistically significant) impact on all ASEAN-5 countries (except for the Philippines), with output elasticities ranging between -0.23 and -0.35 percent. The effects for other countries in the Asia-Pacific region, except for India, are also statistically significant and range between -0.06 and -0.17 percent. The lack of significant spillovers to India (output in India would reduce by less than 0.1 percent after one year) most likely reflects its weak trade links with China, its relatively closed capital account, its narrow financial exposures to the rest of the world, and its oil importer status—hence benefiting from a China-induced fall in oil prices (see International Monetary Fund (2014) for details). Moreover, given the emergence of China as a key driver of the global economy over the past couple of decades, it is not surprising to observe a non-trivial (though smaller) spillover from China to other systemic economies, with average elasticities being -0.12, -0.04, and -0.07 percent for the euro area, U.K., and the U.S., respectively.[8] It appears that countries with large trade exposures to China are most vulnerable to negative shocks to China's GDP. These results are consistent with Cesa-Bianchi et al. (2012), who investigate the impact of China's emergence in the

[8] The results for the other countries in our sample, listed in Table 2, are not reported here, but are available on request.

world economy on Latin American countries' business cycles, while we concentrate on Asian countries and systemic economies, but also the global economy at an aggregated level.[9]

Figure 3: Average Output Elasticities Over the First Year Following a Negative GDP Shock in China (Using Various Weights)

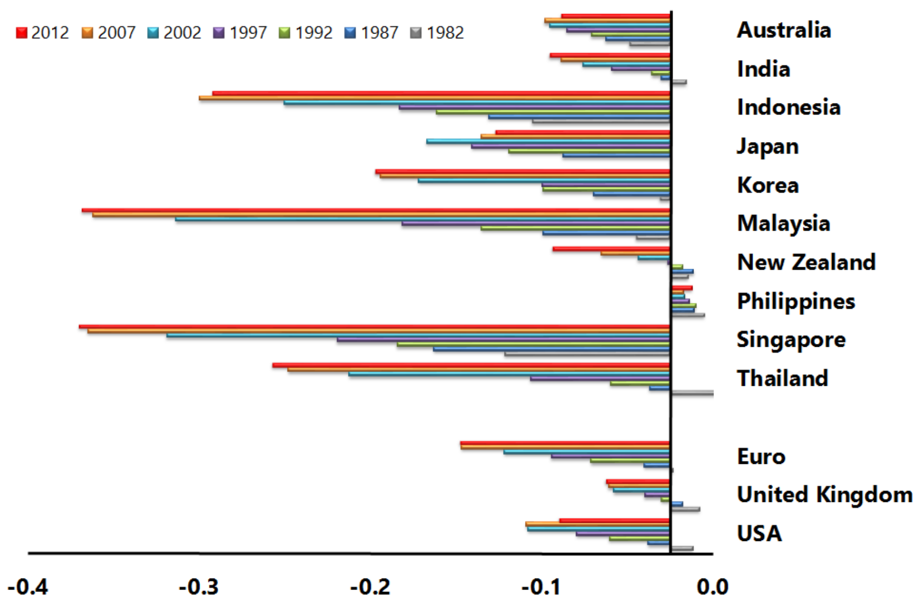


Notes: Depicts the percent change in output of a given country associated with 1% permanent decline in China's GDP, equivalent to a one-off one percent growth shock, together with the 16th and 84th percentile error bands. Mixed weights and trade weights are calculated based on data from 2012 while TiVa weights are computed based on 2009 observations.

We also note that our estimated elasticities in Figure 3 are broadly in line with other exercises based on alternative modelling approaches—see Duval et al. (2014), who report average responses of about 0.3% and 0.15% for median Asian and non-Asian economies, respectively; and Ahuja and Nabar (2012), where the impact on the ASEAN countries are reported to fall between 0.2% and 0.6%. Overall, China' size and its centrality to global value chains mean that any economic slowdown in China will entail global spillovers, especially through trade channels. These trade effects are both direct (reduced bilateral imports by China from its trade partners) and indirect (impact on commodity prices and third-market effects as China is one of the main trading partners (top ten) for over 100 economies that account for about 80 percent of world GDP). It is worth reiterating that our GVAR approach takes into account not only the direct trade exposure of countries to China but also the indirect effects through secondary or tertiary channels (i.e. exchange rates and asset prices).

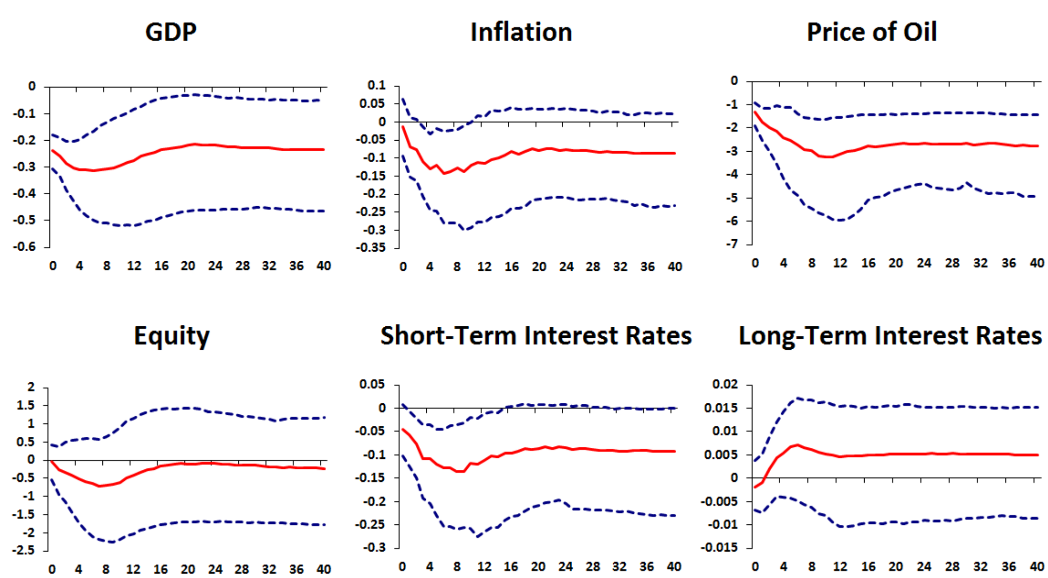
[9]For a conditional forecast analysis of China's hard landing in a GVAR context, see Gauvin and Rebillard (2015).

Figure 4: Average Output Elasticities Over the First Year Following a Negative GDP Shock in China (Using Time-Varying Bilateral Trade Weights)



Notes: Depicts the percent change in output of a given country associated with 1% permanent decline in China's GDP, equivalent to a one-off one percent growth shock.

Figure 5: Implications of a Negative China GDP Shock for the Global Economy



Notes: Figures are median generalized impulse responses to a one standard deviation fall in China's GDP, equivalent to a one-off one percent growth shock, together with the 16th and 84th percentile error bands. The impact is in percentage and the horizon is quarterly.

Comparing these results to alternative configurations of cross-country linkages in the global economy, we set up and estimate the GVAR model using a range of other weights (trade, trade in value added, and financial). More specifically, instead of constructing the foreign variables, $\mathbf{x}_{it}^*$, using bilateral trade weights, w_{ij}, we also considered trade in value weights, and a mixed set of weights for which we used trade weights to construct y_{it}^* and π_{it}^*, but financial weights to construct eq_{it}^*, r_{it}^{*S}, and r_{it}^{*L}. The financial weights are constructed based on bilateral stock of portfolio investment liability positions of countries, covering both equity and debt, derived from the IMF's *Coordinated Portfolio Investment Survey.* As is shown in Figure 3, whether we use trade (labelled Trade), trade in value (labelled TiVa), or financial weights (labelled Mixed) to construct $\mathbf{x}_{it}^*$, the magnitudes of the elasticities across different models are very similar, suggesting that the choice of weights is of second-order importance. We therefore, as is now standard in the GVAR literature, only focus on the results using trade weights. Note that the main justification for using bilateral trade weights, as opposed to financial weights, is that the former have been shown to be the most important determinant of national business cycle comovements, see, for instance, Baxter and Kouparitsas (2005).

To investigate the extent to which the global impact of a China slowdown has changed over the past three decades, we set up and estimate a GVAR model in which the country-specific foreign variables are constructed with time-varying trade weights, while the GVAR model is solved with trade weights for each of the years: 1982, 1987, 1992, 1997, 2002, 2007, and 2012. Figure 4 shows that based on trade weights more than 30 years ago, a negative Chinese output shock would not have had a large effect on either the systemic economies or the Asia-Pacific region. In fact while the estimates based on the weights in the 1980s and 1990s are not statistically significant, they are indeed significant based on the 2002/07/12 weights, see Figure 3.[10] These results indicate that not only does a recent Chinese GDP shock affect the global economy in a much more prominent way, but the median effects are generally much larger than those of three decades ago. This is consistent with the findings in Cesa-Bianchi et al. (2012), who argue that the reason why Latin American economies recovered much faster than initially anticipated from the recent global crisis was due to their increasing trade linkages with China. We also argue that the emergence of China as a driver of growth in the world economy might help to explain the "lower-than-expected" effect of the global financial crisis on Asian countries and other emerging economies (including commodity exporters) and the potential risks China's slowdown pose to these economies going forward.[11]

[10] The figures showing the statistical significance for the different weights are not reported here, but are available from the authors upon request.

[11] See also Cashin et al. (2016).

On commodity prices, Figure 5 shows a significant fall in oil prices in response to a negative China output shock, with oil prices falling by 2.8 percent below their pre-shock levels. This suggests that China's rebalancing affects the economies of commodity exporters in our sample mainly through its impact on global demand for commodities and associated prices.[12] For these countries, the slowdown in China translates into lower overall economic growth.[13] Overall, the results show that following a permanent 1% negative Chinese GDP shock, global growth reduces by 0.23% in the short run. There is also evidence for a short-run fall in both global inflation and short-term interest rates, however, while the median effect on global equity prices is negative, it is not statistically significant (see Figure 5).

4 The Effects of A Surge in Global Financial Market Volatility

Excessive global financial market volatility could emanate from disorderly macro-financial developments in China (see, for instance, De Bock and de Carvalho Filho 2015), and/or if advanced countries' monetary policy tightening takes an uncertain turn, or occurs at an accelerated pace, especially given the already increased capital flows into emerging market economies. The VIX spiked in August 2015, when China's stock market prices fell sharply despite official support, and the renminbi fixing mechanism was adjusted, leading to renminbi depreciation vis-à-vis the U.S. dollar. Another global financial market volatility episode occurred in January 2016 coinciding with another large price decline in China's stock market. In the summer of 2013, an indication by the U.S. Federal Reserve of plans to taper its securities-purchase program created a surge in global financial market volatility, and resulted in adverse spillovers to emerging market economies. Countries that experienced rapid capital inflows and strong currency appreciation pressures during 2010–12 saw a sharp reversal in the 2013 episode of market volatility. Given that the risk of excessive market volatility remains in 2017, we also examine the international spillover effects of surges in global financial market volatility on the world economy without trying to identify the cause of the shock.

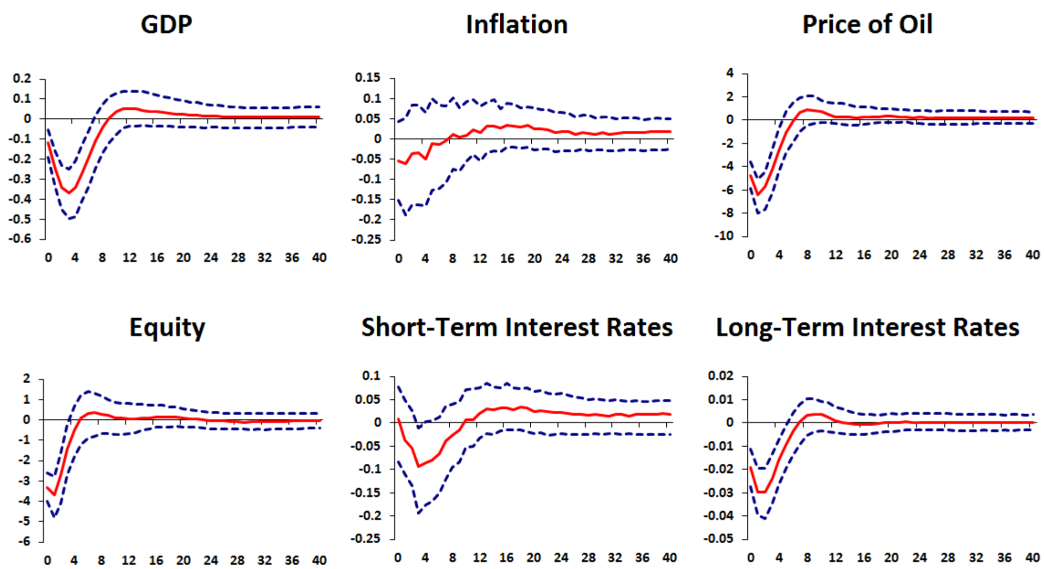
Figure 6 shows that a one standard deviation shock to the financial stress index (FSI_t) translates into a short-run lower overall economic growth globally. Specifically, our estimates suggest that world output falls on average by 0.29% below the pre-shock level in the first four quarters after the surge in global financial market volatility, with this effect being statistically

[12] See Cashin et al. (2014), Mohaddes and Pesaran (2016a), and Mohaddes and Raissi (2015) for a detailed discussion on the effects of oil prices on growth.

[13] See also Roache (2012) and International Monetary Fund (2012) for a detailed discussion on the outward spillovers from China through commodity price channels.

significant. Not surprisingly we also observe that this shock causes oil prices to fall (-6.5%) and it has a negative short-run effect on global equity prices (-3.7%) and long-term interest rates (-0.03%), reflecting increased risk aversion (the numbers in the brackets correspond to the peak effects in the first quarter). Moreover, a widening of the output gap and lower commodity prices likely moderate global inflation slightly.

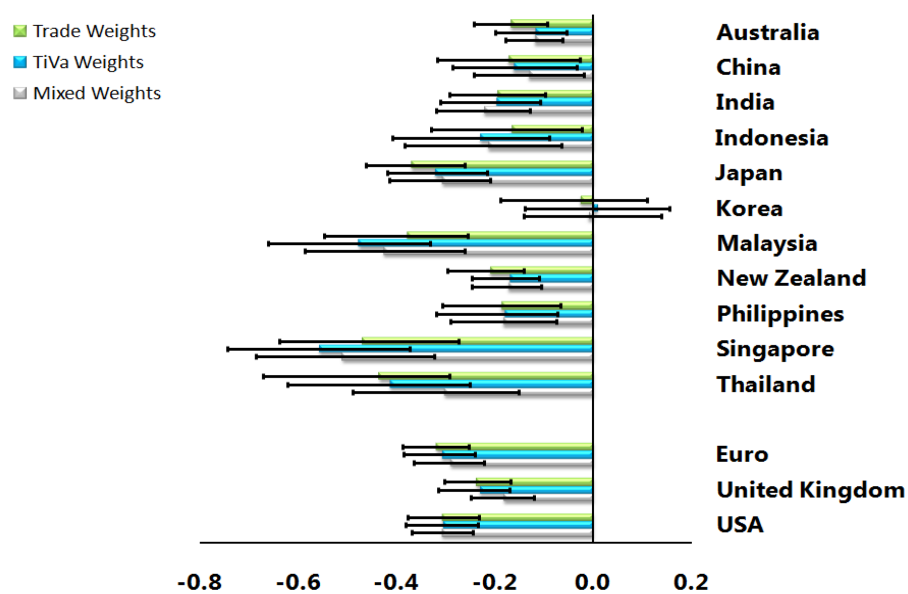
Figure 6: Implications of an Increase in Financial Market Volatility for the Global Economy



Notes: Figures are median generalized impulse responses to a one standard deviation increase in FSI_t, together with the 16th and 84th percentile error bands. The impact is in percentage and the horizon is quarterly. The magnitude of the shock is comparable to the 2002 episode of market volatility in advanced economies and is much smaller than the Global Financial Crisis shock.

We next turn to the implications of a sharp increase in global financial market volatility for individual countries. Figure 7 reports the average output responses to a one standard deviation increase in FSI_t over the first year, together with the 16th and 84th percentile error bands. We notice that there are significant heterogeneities across countries in terms of their impulse responses. In Asia, output falls between 0.17 and 0.47 percent below the pre-shock level, with these effects being statistically significant for all countries except for Korea, operating though trade and financial linkages. It is worth highlighting that the effects on China and Japan are relatively larger, as real output falls by around 0.17 and 0.37 percent on average respectively over the first year. The commodity-price channel also leads to an adverse impact on economic activity in commodity exporters (as oil prices fall by about 6.5 percent in the first quarter, see Figure 6), with both Australia and New Zealand experiencing a fall in economic activity of 0.17 and 0.21 percent respectively. Even economic activity in large commodity importers are affected, as real output in India falls by about 0.19 percent on average over the first year following the shock. Finally, our estimates suggest that the FSI shock leads to output falling by 0.32, 0.24 and 0.31 percent for the euro area, the U.K., and the U.S. respectively. These results echo those reported in Dovern and van Roye (2013), who illustrate that financial stress has significant negative effects on economic activity (as measured by industrial production) for all of the 20 countries in their model. Interestingly the magnitude of the responses are also in line with those depicted in Figure 7.

Figure 7: Average Output Responses to an Increase in Global Financial Market Volatility over the First Year (Using Various Weights)



Notes: Depicts the percent change in output of a given country associated with a one standard deviation increase in FSI_t, together with the 16th and 84th percentile error bands. The magnitude of the shock is comparable to the 2002 episode of market volatility in advanced economies and is much smaller than the Global Financial Crisis shock.

We argue that while strong fundamentals and sound policy frameworks are important, they cannot fully isolate countries from the effects of a sharp increase in global financial market volatility. This is particularly the case where there is a sudden adjustment of expectations triggered by monetary policy normalization uncertainty in advanced economies. This argument is supported by the output responses in Figure 7, where no country (neither advanced nor emerging market economies) appears immune from the impact of a surge in global financial market volatility.

Finally, we allow for alternative configurations of cross-country linkages in the global economy and therefore, in addition to bilateral trade weights, we also estimate the individual country models using trade in value weights as well as mixed weights (using a combination of trade and financial weights), and find that the magnitudes of the impulse responses and their direction are generally very similar (see Figure 7).

5 Concluding Remarks

Estimating a GVAR model for 26 countries/regions over the period 1981Q1–2013Q1, we analyzed the global macroeconomic implications of China's slowdown and the consequences of a surge in global financial market volatility. While the estimated spillovers from China's slowdown to the rest of the world are negative, there are considerable heterogeneities across countries (generally, those with large trade exposures to China are the most affected). Specifically: (i) the impact on ASEAN-5 countries (except for the Philippines) is the largest, with growth elasticities ranging between -0.23 and -0.35 percentage points; (ii) the growth effects for the other countries in the Asia-Pacific region, except for India, are also statistically significant and fall between -0.06 and -0.17 percentage points; and (iii) while the estimated China growth spillovers to other systemic countries are smaller, they are not trivial—with average elasticities being -0.12, -0.04, and -0.07 percentage points for the euro area, U.K., and the U.S., respectively. Overall, a 1% permanent negative Chinese GDP shock reduces global growth by 0.23 percentage points in the short run. Moreover, oil prices fall by 2.8% and there is a short-run fall in both global inflation and short-term interest rates.

In addition, we showed that growth-spillover elasticities have become larger over time, reflecting the direction of evolving trade patterns, and China's growing role in the global economy and world commodity markets. Moreover, we illustrated that a sharp increase in global financial market volatility could translate into: (i) a short-run lower overall world economic growth of around 0.29 percentage points; (ii) lower global equity prices, long-term interest rates, and oil prices; and (iii) significant negative spillovers to emerging market economies (operating through trade and financial linkages).

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