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China's Emergence in the World Economy and Business Cycles in Latin America

As vividly illustrated by the impact of the recent global crisis on Latin America, the international business cycle is very important for the region's economic performance.[1] The world economy, however, has undergone profound structural changes over the past two to three decades because of globalization and the emergence of China, India, and other large developing economies (including Mexico and Brazil in Latin America) as global economic players. As a result, the transmission mechanisms of the international business cycle to Latin America may have changed.

This paper focuses on the emergence of China as a global force in the world economy and investigates how changes in trade patterns between China and the rest of the world may have affected the transmission of the international business cycle to Latin America. Specifically, we investigate empirically how shocks to gross domestic product (GDP) in China and the United States are transmitted to Latin America, conditional on alternative configurations of cross-country linkages in the world economy. We focus on China because its trade linkages with Latin America and the rest of the world have undergone the most dramatic shift over the period we consider. We focus on the United States because this country remains the largest trading partner of the Latin

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1. For empirical analyses of the impact of external factors on Latin American economic performance, see Little and others (1993), Hoffmaister and Roldos (1997), Rebucci (1998), Canova (2005), Österholm and Zettelmeyer (2007), and Izquierdo, Romero, and Talvi (2008).

American region as a whole and, historically, has been the major source of external shocks for Latin America. To complement this analysis, we also consider a GDP shock to the Latin American region itself and to emerging Asia (excluding China and India) because the analysis of these shocks helps shed light on the ongoing debate about the decoupling of emerging markets' business cycle from that of advanced economies.

To conduct the empirical analysis, we use a variant of the global vector autoregressive (GVAR) model originally proposed by Pesaran, Schuermann, and Weiner and further developed by Dees and others.[2] This is a relatively novel approach to global macroeconomic modeling that combines time series, panel data, and factor analysis techniques, which can be used to address a wide set of issues.[3] In the first step of the methodology, each country is modeled individually as a small open economy 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 the international price of oil). In the second step, a global model is constructed combining all the estimated country-specific models and linking them with a matrix of predetermined (that is, not estimated) cross-country linkages. Consistent with the existing GVAR literature and the main purpose of the application in this paper, we use trade shares to quantify the linkages among all the economies included in the GVAR model.[4]

The shocks that we investigate are not structural. However, given that our focus is on the transmission of GDP shocks across countries, the issue of identifying the sources of the shocks (whether they are due to demand, supply, productivity, or monetary policy) is not central to our analysis. The GVAR model that we use identifies the country-specific shocks by conditioning each variable on contemporaneous values of foreign-specific variables, which

2. Pesaran, Schuermann, and Weiner (2004); Dees and others (2007).

3. The GVAR approach can be used to address a wide range of questions. For instance, Dees and others (2007) study the transmission to the euro area of shocks to U.S. real equity prices, short-term interest rates, and oil prices. Pesaran, Schuermann, and Smith (2009a) consider the problem of forecasting economic and financial variables across a large number of countries in the global economy. Xu (2012) investigates the impact of a credit crunch in the United States on advanced and emerging market economies, including Asia and Latin America. Cesa-Bianchi (2012) studies the international transmission of house price shocks. Cesa-Bianchi, Powell, and Rebucci (2011) use the GVAR as a filter to identify non-fundamental movements in equity prices in the global economy.

4. Trade in goods represents the most important quantifiable channel through which shocks are transmitted across countries.

renders the cross-country dependence of the shocks weak and of second-order importance.

A novel, methodological contribution of this paper is to 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. This allows us to study and compare the impact of GDP shocks with alternative configurations of cross-country linkages and to investigate how the transmission of shocks has changed since the emergence of China in the world economy. Specifically, we simulate GDP shocks in the GVAR model using trade weights at different points in time, thus capturing the fundamental aspect of China's rapidly changing role in the world economy: namely, its new pattern of trade linkages with Latin America and the rest of the world. The paper also provides a new procedure for bootstrapping the estimated parameters with time-varying weights. The use of time-varying weights is important in our application not only because it allows us to account for the fast evolution of trade relations in the world economy, but more generally because it enhances parameter stability, which in turn supports more reliable counterfactual simulation exercises. According to our empirical findings, standard statistical tests do not detect significant parameter instability in the GVAR model we estimate, even for Latin American economies that have experienced frequent changes in policy regimes and other deep structural changes.

In our application, the GVAR model is applied to twenty-five major advanced and emerging economies plus the euro area, covering more than 90 percent of world GDP. This sample includes five large Latin American economies: Argentina, Brazil, Chile, Mexico, and Peru. The data set is quarterly, from 1979:2 to 2009:4, thus including both the recession of 2008–09 and the first few quarters of the global recovery.[5]

The main results of the empirical analysis are fourfold. First, the long-run impact of a Chinese GDP shock on the five Latin American economies has increased dramatically (by three times) since the mid-1990s. Second, and consistent with the previous result, the long-run effect of a U.S. GDP shock on Latin America has halved over the same period, with even sharper declines in the short term. Third, the transmission of domestic shocks originating in Latin America or the rest of emerging Asia (excluding China and India) has not changed over the period. Finally, the results predict that

5. The dataset and the GVAR code used for our analysis are available online at www-cfap.jbs.cam.ac.uk/research/gvartoolbox/index.html.

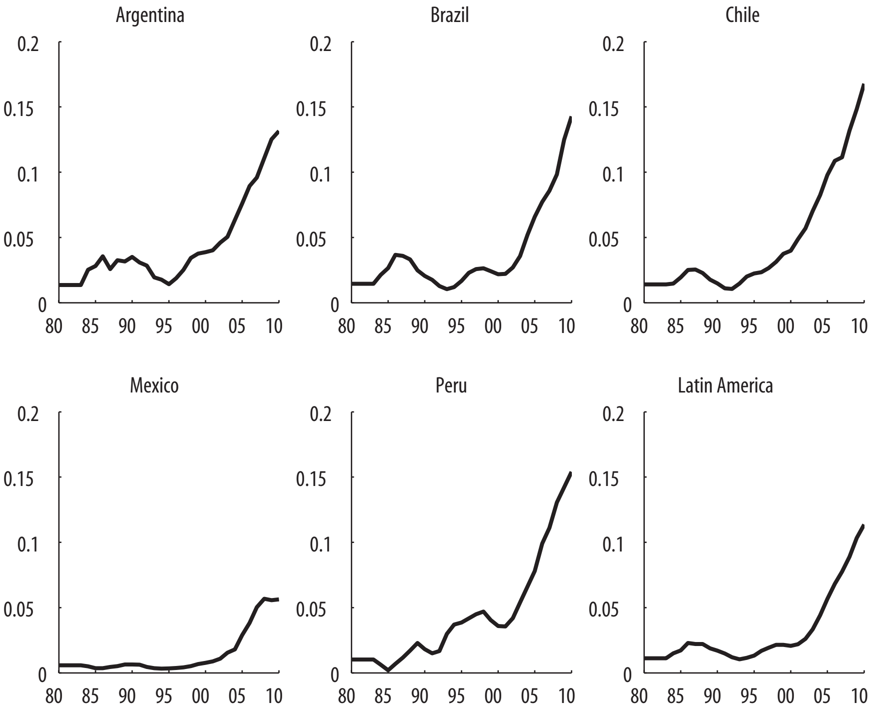
the increased impact of a Chinese GDP shock on Latin America owes as much to indirect effects, which are associated with stronger trade linkages between China and Latin America's largest trading partners (namely, the United States and the euro area), as to direct effects that stem from tighter trade linkages between China and Latin America, boosted by the decade-long boom in commodity prices.

These findings have important policy implications for Latin America. First, they help to explain why these five Latin American economies recovered much faster than initially anticipated from the recent global crisis. The evidence shows that Latin American growth owes more to a fast-growing economy that enacted a powerful fiscal stimulus during the global crisis (China), and relatively less to the economy that was at the epicenter of the crisis (the United States). Had the trade linkages been those prevailing in the mid-1990s, the region would have suffered a much sharper downturn than it actually experienced. This evidence also suggests that the so-called decoupling found in the existing literature might be related to the emergence of China as an important source of world growth, as opposed to a widespread decoupling of business cycles in emerging and advanced economies.[6] Second, the results point to hidden vulnerabilities. Latin America remains a small open economy vulnerable to external shocks, without the necessary weight to affect the international business cycle with its own growth dynamics. While the changes documented here have had positive, stabilizing effects on Latin America's business cycle during the recent global crisis, they predict negative, destabilizing effects if and when China's growth begins to slow significantly, especially if this happens before the United States and the euro area have fully recovered from the global crisis.

The rest of the paper is organized as follows. In the next section, we discuss how the trade linkages between China and the rest of the world, particularly Latin America, have evolved over time, thus justifying the specific set of trade matrices we use in the counterfactual simulations. We then describe the GVAR methodology that we use, discuss the estimation and testing of the GVAR model, and report the counterfactual simulation results. The final section concludes. Three appendices describe the construction of the data set, explain the econometric methodology and bootstrap procedure used, and report additional estimation and bootstrapped results for the GVAR model with time-varying weights.

6. See, for example, Kose and Prasad (2010).

FIGURE 1. China's Share in Latin America's Total Annual Trade, 1980–2009
Percent



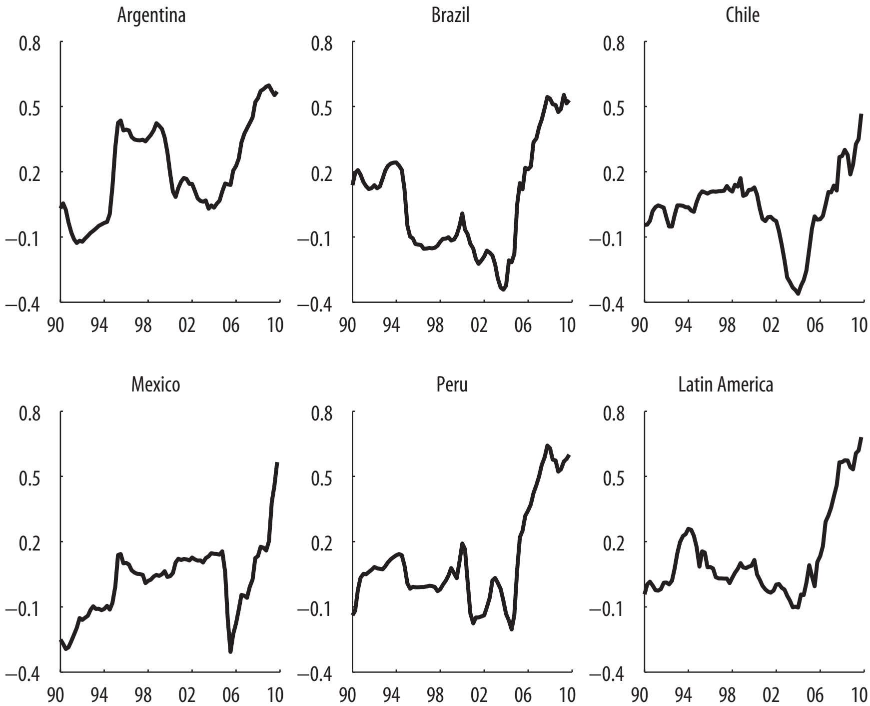
The Changing Weight of China in Latin America and World Trade

The importance of China for Latin America's trade has increased more than three-fold over the past thirty years or so, from roughly 1 percent in 1980 to more than 12 percent in 2009 (figure 1).[7] The takeoff of China's trade with Latin America, however, starts only in the mid-1990s, with little or no change in the previous decade.[8]

7. The changing economic relationship between China and Latin America is discussed in Devlin, Estevadeordal, and Rodríguez-Clare (2006).

8. The trade share of country *i* in country *j*'s total trade is defined as the sum of country *i*'s imports from country *j* and exports to country *j,* divided by the sum of country *j*'s total merchandise imports and exports. The available trade statistics for the relevant countries and time periods only cover trade in goods, thus omitting trade in services. Also, the trade statistics are net of transit trades.

FIGURE 2. Comovements between Latin American and Chinese GDP Growth[a]



a. The figures graph the ten-year moving correlation of annual growth rates, from 1990:1 to 2009:4.

Growing bilateral trade linkages between China and Latin America are also associated with more synchronized business cycles over the last fifteen years or so.[9] Figure 2 plots a rough measure of business cycle synchronization (namely, a ten-year rolling window correlation between Latin American and Chinese GDP growth), showing a steady increase from the beginning of the 1990s to the end of the sample period in 2009.[10] In 2009, the average rolling correlation for Latin America was four times higher than in 1995, increasing from 0.12 to 0.61. Furthermore, all five Latin American countries

9. As mentioned in the introduction, the five Latin American countries included in our sample are Argentina, Brazil, Chile, Mexico, and Peru.

10. Latin America's regional GDP growth is calculated as a weighted average of individual countries' GDP using PPP-GDP weights averaged over the period 2006–08 (sourced from the World Bank's World Development Indicators database).

considered display a pattern similar to the regional one. Even in the case of Mexico, which belongs to the North American Free Trade Agreement (NAFTA) and hence has stronger ties with the United States, the correlation changed from around 0.1 in 1995 to around 0.4 in 2009, while in the case of Brazil it increased from about –0.1 to 0.5.[11]

While China is undoubtedly more important for Latin America's business cycle now than fifteen years ago, how much more important is it? In particular, does it affect the cycle through its direct, bilateral trade linkages or through other indirect channels of interdependence? For instance, Calderón finds that China affects Latin America's business cycle mostly via its demand for commodities.[12] Consequently, the decade-long commodity price boom might be inflating the bilateral trade shares between China and Latin America, as plotted in figure 1. Other potentially important indirect channels of influence are related to international capital flows and China's exchange rate regime.[13]

The available trade statistics confirm that China has played an increasing role over the past fifteen years not only directly, but also indirectly via its increased importance for Latin America's traditional and largest trading partners, such as the United States and the euro area. Tables 1 and 2 report a complete set of trade shares for the United States, the euro area, Japan, China, the five Latin American countries in our sample, and the rest of the world at two different points in time, 1995 and 2009. The tables measure integration by total trade, as opposed to exports only. Table 1, which features the major trade blocs, shows that the United States and the euro area continue to be Latin America's largest partners by a sizable margin: at the end of 2009, the United States and the euro area together accounted for more than 60 percent of total Latin American trade (the United States 51 percent and the euro area 15 percent), after declining from almost 80 percent in 1995 (when U.S. and euro area weights were 60 percent and 18 percent, respectively). The table further shows that China's emergence as a global trade power has affected Latin America's largest trading partners: China's share in total trade of the United States, the euro area, and Japan grew from 5 percent, 4 percent, and 9 percent in 1995, respectively, to 18 percent, 15 percent, and 26 percent in 2009. Finally, when the trade bloc shares are disaggregated by country (table 2), China's share of

11. Calderón (2008) reports similar evidence (through year-end 2004).
12. Calderón (2008).
13. See Cova, Pisani, and Rebucci (2010) and Izquierdo and Talvi (2011) for a more detailed discussion.

TABLE 1. Trade Shares for Major Trading Blocs in 2009 and 1995[a]

Year and trading bloc	*United States*	*Euro area*	*Japan*	*China*	*Latin America*
A. 2009					
United States	—	0.17	0.18	0.22	0.51
Euro area	0.15	—	0.11	0.18	0.15
Japan	0.07	0.05	—	0.15	0.04
China	0.18	0.15	0.26	—	0.12
Latin America	0.18	0.06	0.03	0.05	—
Rest of the world	0.42	0.58	0.42	0.39	0.18
Total	1.00	1.00	1.00	1.00	1.00
B. 1995					
United States	—	0.19	0.31	0.21	0.60
Euro area	0.16	—	0.13	0.17	0.18
Japan	0.17	0.09	—	0.30	0.07
China	0.05	0.04	0.09	—	0.02
Latin America	0.13	0.05	0.03	0.02	—
Rest of the world	0.50	0.63	0.43	0.29	0.13
Total	1.00	1.00	1.00	1.00	1.00

Source: International Monetary Fund (IMF), Direction of Trade Statistics.

a. The Latin American bloc comprises the five countries in our sample (Argentina, Brazil, Chile, Mexico, and Peru). The trade share of country *i* with respect to country *j* is defined as the sum of country *i*'s imports from country *j* and exports to country *j* divided by the sum of country *i*'s total imports and exports. They are displayed in columns by country such that a column sums to one.

TABLE 2. Trade Shares for Latin American Countries in 2009 and 1995[a]

Year and trading partner	*Argentina*	*Brazil*	*Chile*	*Mexico*	*Peru*
A. 2009					
United States	0.12	0.17	0.20	0.70	0.25
Euro area	0.17	0.23	0.16	0.07	0.14
Japan	0.02	0.05	0.08	0.02	0.06
China	0.13	0.16	0.18	0.06	0.16
Other Latin American countries	0.43	0.17	0.20	0.03	0.20
Rest of the world	0.13	0.21	0.18	0.12	0.18
Total	1.00	1.00	1.00	1.00	1.00
B. 1995					
United States	0.16	0.25	0.23	0.83	0.29
Euro area	0.26	0.28	0.21	0.06	0.22
Japan	0.03	0.08	0.14	0.03	0.08
China	0.03	0.03	0.02	0.00	0.05
Other Latin American	0.39	0.18	0.20	0.02	0.19
Rest of the world	0.13	0.18	0.19	0.06	0.18
Total	1.00	1.00	1.00	1.00	1.00

Source: IMF, Direction of Trade Statistics.

a. Trade weights are computed as shares of exports and imports. They are displayed in columns by country such that a column sums to one.

total trade surged in all the Latin American countries except Mexico (which recorded only a moderate increase) over the same period, and this shift mostly occurred at the expense of the United States and the euro area.

This stylized evidence suggests that China today might be affecting Latin America's business cycle not only via its stronger direct trade linkages, but also through its stronger indirect linkages with the region's main traditional trading partners. In the rest of the paper, we quantify how these changes in the geographical composition of trade have affected the transmission of specific shocks to Latin America and the rest of the world economy. We also attempt, to the extent possible, to disentangle direct effects stemming from commodity price increases and the indirect effects of the increased influence on traditional trading partners.[14]

The GVAR Methodology

In this section, we present the GVAR methodology and discuss some of its underlying assumptions, the nature of the counterfactual experiments conducted, and the type of shocks to be considered.

The GVAR modeling strategy consists of two main steps. First, each country is modeled individually as a small open economy by estimating a country-specific vector error correction model in which domestic variables are related to both country-specific foreign variables and global variables that are common across all countries (such as the price of oil). The foreign variables provide the link between the evolution of the domestic economy and the rest of the world and, in the country-specific model estimations, are taken as (weakly) exogenous—an assumption that is tested in the paper. Second, a global model is constructed combining all the estimated country-specific models and linking them with a matrix of predetermined (that is, not estimated) cross-country linkages. We now present and discuss each of these two steps in turn.[15]

14. Other indirect transmission channels, such as financial linkages, are taken into account in the GVAR model through the inclusion of financial variables, but they are not discussed separately in the paper because comparable counterfactual simulation exercises to those used to investigate trade linkages cannot be constructed, given the limited availability of reliable data on bilateral financial positions.

15. See Dees and others (2007) and Garratt and others (2006) for a detailed illustration of the GVAR methodology.

The First Step: Specification and Estimation of Country-Specific Models

Consider $N + 1$ countries in the global economy, indexed by $i = 0, 1, 2, \ldots N$. In the first step, with the exception of country 0 (which in our application is the United States), all other N countries are modeled as small open economies in which a set of domestic variables ($\mathbf{x}_{it}$, to be specified below) is related to a set of country-specific foreign variables, $\mathbf{x}^*_{it}$, using an augmented vector autoregressive model (VARX*) specification. Specifically, for each country i, we set up a VARX*(p_i, q_i) model in which the $k_i \times 1$ vector, $\mathbf{x}_{it}$, is related to the $k^*_i \times 1$ vector of country-specific foreign variables, $\mathbf{x}^*_{it}$, and the $m_d \times 1$ global variables, $\mathbf{d}_t$, plus a constant and a deterministic time trend:

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

with $t = 0, 1, 2, \ldots T$. Here $\boldsymbol{\Phi}_i(L,p_i) = I - \sum_{i=1}^{pi}\boldsymbol{\Phi}_i L^i$ is the matrix lag polynomial of the coefficients associated with $\mathbf{x}_{it}$; $\mathbf{a}_{i0}$ is a $k_i \times 1$ vector of fixed intercepts; $\mathbf{a}_{i0}$ is the $k_i \times 1$ vector of coefficients on the deterministic time trends; $\boldsymbol{\Upsilon}_i(L,q_i) = \sum_{i=0}^{qi}\boldsymbol{\Upsilon}_i L^i$ is the matrix lag polynomial of the coefficients associated with $\mathbf{d}_t$; $\boldsymbol{\Lambda}_i(L,q_i) = \sum_{i=0}^{qi}\boldsymbol{\Lambda}_i L^i$ is the matrix lag polynomial of the coefficients associated with $\mathbf{x}^*_{it}$; $\mathbf{u}_{it}$ is a $k_i \times 1$ vector of country-specific shocks, which we assume to be serially uncorrelated, with zero mean and a nonsingular covariance matrix, Σ_{it}, namely, $\mathbf{u}_{it} \sim$ i.i.d$(0, \Sigma_{it})$.[16]

The vector of country-specific foreign variables, $\mathbf{x}^*_{it}$, plays a central role in the GVAR methodology. Consistent with the existing GVAR literature, for each country i at each time t, this vector is constructed as the weighted average across all countries j of the corresponding variables in the model ($\mathbf{x}_{it}$ for $j \neq i$). As a way of dealing with the curse of dimensionality when N is relatively large, the weights used in the construction of $\mathbf{x}^*_{it}$ are not estimated, but specified a priori based on information that measures the strength of bilateral linkages in the global economy. While the GVAR methodology can be implemented with any set of weights, the existing GVAR literature uses trade weights, as does the application in this paper. Specifically, the weight of country j in the foreign variables of country i is given by the share of country j in the total trade of country i (as described in footnote 8).

The choice of trade weights is based on a number of considerations. First, trade in goods represents an important (if not the most important) channel through which shocks are transmitted across countries. Second, trade link-

16. We allow $\boldsymbol{\Phi}_i(L,p_i)$, $\boldsymbol{\Upsilon}_i(L,q_i)$, and $\boldsymbol{\Lambda}_i(L,q_i)$ to differ across countries. The lag orders, p_i and q_i, are also selected on a country-by-country basis.

ages tend to reflect technological, political, and cultural linkages between countries and provide a good measurable proxy for such interconnections. Third, among the alternative measures that could be used, trade weights are perhaps the most reliable, and data sources are readily available to quantify them. Reliable bilateral trade statistics are published annually for all countries (with a few exceptions), while data on bilateral financial flows are either non-existent or much more volatile and less reliable, as their collection has started only recently. The use of bilateral financial flows could therefore exaggerate the cross-country transmission of shocks and lead to parameter instability. Finally, trade integration started much earlier than financial integration and has been present throughout our sample period. China, the main focus of this paper, has affected the rest of the world dramatically through its expansion, and yet its financial system is not internationally connected. The same applies to other emerging market economies in our model.

In the case of a GVAR model comprising small open economies, the choice of weights is of secondary importance for the estimation of country-specific parameters, particularly since the variables tend to be highly correlated across countries. As shown by Pesaran, for sufficiently large N, the estimation results are asymptotically invariant to the choice of weights so long as they are granular, namely of order $1/N$.[17] As the application in this paper shows, however, the impulse response of shocks to a particular variable in the GVAR does depend on the choice of weights even if similar parameter estimates are obtained using different sets of weights. This is a particularly important consideration for the present paper, which focuses on the possible effects of changing trade linkages between Latin America and the world economy.

With this in mind, we develop a GVAR model in which trade weights are allowed to change both at the estimation stage and at the solution stage (when impulse responses are computed), whereas most other GVAR applications to date are based on fixed trade weights. This methodological innovation is important as it allows us to take into account the evidence that trade integration has progressed over time and that the geographical patterns of trade changed dramatically with the acceleration of globalization in the mid-1990s, as documented earlier. Specifically, when estimating the parameters of the GVAR model, the $\mathbf{x}_{it}^*$ are constructed as follows:

$$\mathbf{x}_{it}^*\left(\mathbf{W}_{i,\tau(t)}\right) = \sum_{j=0}^{N} \mathbf{W}_{ij,\tau(t)}\mathbf{x}_{jt} = \mathbf{W}_{i,\tau(t)}\mathbf{x}_t, \tag{2}$$

17. Pesaran (2006).

where $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, \ldots, \mathbf{x}'_{Nt})'$ is the $k \times 1$ vector of the endogenous variables ($k = \sum_{i=0}^{N} k_i$); $\mathbf{W}_{ij,\tau(t)}$ is the $k_i^* \times k_j$ matrix that contains the trade weights of country j in country i at time t, for a given $\tau(t)$; and $\mathbf{W}_{i,\tau(t)} = (\mathbf{W}_{i0,\tau(t)}, \mathbf{W}_{i1,\tau(t)}, \ldots, \mathbf{W}_{iN,\tau(t)})$ with $\mathbf{W}_{ii,\tau(t)} = 0$ is the $k_i^* \times k$ weights matrix for country i at time t. Here $\tau(t)$ is a generic rule that indexes the time-varying weights at each time period t. For instance, in our empirical application, for each quarter t, $\tau(t)$ refers to three-year average trade weights for the current year, t, and the previous two years, $t-1$ and $t-2$.[18] For each choice of weight matrix, $\mathbf{W}_{i,\tau(t)}$, $\mathbf{x}_{it}^*(\mathbf{W}_{i,\tau(t)})$ and its lagged value are constructed according to equation 2, and it is not necessarily the case that $\mathbf{x}_{i,t-1}^*$ is equal to the lagged value of $\mathbf{x}_{it}^*$. This is only true if the weights are time invariant.[19]

Equipped with this notation, equation 1 can be rewritten as[20]

$$(3) \quad \mathbf{x}_{it} = \mathbf{\Phi}_i \mathbf{x}_{i,t-1} + \mathbf{\Lambda}_{i0} \mathbf{W}_{i,\tau(t)} \mathbf{x}_t + \mathbf{\Lambda}_{i1} \mathbf{W}_{i,\tau(t-1)} \mathbf{x}_{t-1} + \mathbf{u}_{it}, \text{ for } i = 0,1,2,\ldots N.$$

For a given set of weights, the error correction representation of the country-specific models in equation 3 can be tested for cointegration and estimated following Harbo and others and Pesaran, Shin, and Smith.[21] Using the sample $\mathbf{x}_t = 1, 2, \ldots T$, such estimates can be denoted by $\hat{\mathbf{\Phi}}_i$, $\hat{\Lambda}_{i0}$, and $\hat{\Lambda}_{i1}$, with associated country-specific residuals

$$(4) \quad \hat{\mathbf{u}}_{it} = \mathbf{x}_{it} - \hat{\mathbf{\Phi}}_i \mathbf{x}_{i,t-1} - \hat{\mathbf{\Lambda}}_{i0} \mathbf{W}_{i,\tau(t)} \mathbf{x}_t - \hat{\mathbf{\Lambda}}_{i1} \mathbf{W}_{i,\tau(t-1)} \mathbf{x}_{t-1}, t = 2, 3, \ldots T.$$

The country-specific foreign variables are assumed to be weakly exogenous for the purpose of estimating the parameters of country-specific models. The results of testing the weak exogeneity assumption are reported below and are shown to hold in most cases. These test outcomes are important since they allow each country model to be estimated separately from the rest. In eco-

18. For example, for t at 1989:4, $\tau(t)$ refers to the three-year average trade weights of 1987, 1988, and 1989; for t at 1990:1, $\tau(t)$ refers to the three-year average trade weights of 1988, 1989 and 1990. The three-year moving average is chosen to smooth variations of trade data over time.

19. When the trade weights are constant over time, equation 2 reduces to the more familiar weighted-average definition of $\mathbf{x}_{it}^* = \mathbf{W}_i \mathbf{x}_t = \Sigma_{j=0}^{N} \omega_{ij} \mathbf{x}_{jt}$ used in the previous GVAR literature (see, for instance, Dees and others, 2007).

20. To simplify the exposition here, we abstract from common observed variables and deterministic components and consider a first-order VARX* specification.

21. Harbo and others (1998); Pesaran, Shin, and Smith (2000).

nomic terms, the weak exogeneity assumption permits treating each country as a small open economy with respect to the rest of the world. While the number of countries does not need to be large to build a GVAR model, the weak exogeneity assumption may not be satisfied for all countries if the sample is relatively small. It is only when the number of countries is relatively large (technically, tending to infinity) and all countries are comparable in size that we can have a fully symmetric treatment of all the models in the GVAR. We therefore treat the United States differently as a dominant economy, consistent with previous GVAR applications.

The Second Step: Building the GVAR

In the second step, the GVAR model is set up by stacking the estimated individual country-specific models and linking them with a matrix of predetermined cross-country linkages. Having estimated the country-specific parameters using the time-varying weights, the estimated country-specific models can now be combined and solved for any given trade weights based either on a particular year or on an average of weights from different time periods. In what follows, denote such a link weight matrix by $\mathbf{W}_i^0$, with $i = 0, 1, \ldots N,$ and define the $k_i \times k$ selection matrix $\mathbf{S}_i$ such that

$$\mathbf{x}_{it} = \mathbf{S}_i \mathbf{x}_t . \tag{5}$$

Then rewrite equation 3 in terms of $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, \ldots, \mathbf{x}'_{Nt})'$, which contains all the endogenous variables in the global model:

$$\mathbf{S}_i \mathbf{x}_t = \hat{\mathbf{\Phi}}_i \mathbf{S}_i \mathbf{x}_{t-1} + \hat{\mathbf{\Lambda}}_{i0} \mathbf{W}_i^0 \mathbf{x}_t + \hat{\mathbf{\Lambda}}_{i1} \mathbf{W}_i^0 \mathbf{x}_{t-1} + \tilde{\mathbf{u}}_{it},$$

or

$$\mathbf{G}_i \mathbf{x}_t = \mathbf{H}_i \mathbf{x}_{t-1} + \tilde{\mathbf{u}}_{it}, \tag{6}$$

where

$$\mathbf{G}_i = \mathbf{S}_i - \hat{\mathbf{\Lambda}}_{i0} \mathbf{W}_i^0 \tag{7}$$

and

$$\mathbf{H}_i = \hat{\mathbf{\Phi}}_i \mathbf{S}_i + \hat{\mathbf{\Lambda}}_{i1} \mathbf{W}_i^0 . \tag{8}$$

Now stacking equation 6 for $i = 0, 1, \ldots N,$ we have

$$\mathbf{G}\mathbf{x}_t = \mathbf{H}\mathbf{x}_{t-1} + \tilde{\mathbf{u}}_t, \tag{9}$$

where $\mathbf{G} = (\mathbf{G}_0', \mathbf{G}_1', \ldots, \mathbf{G}_N')'$ and $\mathbf{H} = (\mathbf{H}_0', \mathbf{H}_1', \ldots, \mathbf{H}_N')'$.

Finally, assuming then that $\mathbf{G}$ is nonsingular, we obtain

$$\mathbf{x}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{G}^{-1}\tilde{\mathbf{u}}_t, \tag{10}$$

where $\mathbf{F} = \mathbf{G}^{-1}\mathbf{H}$. The GVAR model in equation 10 can then be used to compare impulse responses for any set of link matrices $\mathbf{W}_i^0$, $i = 0, 1, \ldots N$.[22]

Several remarks are in order. First, given that we are interested in the impact of changing trade patterns on the transmission of shocks of global relevance, we propose to solve the GVAR (estimated in the first step) for weights or link matrices at different points in time. Thus, in the empirical section of the paper, we consider the implications of the same estimated country-specific models for different choices of trade weights. The GVAR model parameters are only estimated in the first stage and are taken as given in the second stage. Under the assumption that these parameters are stable over time, the global model can be safely used counterfactually with alternative trade matrices, as we do in our application.

Second, each alternative trade matrix represents a particular counterfactual of interest that leads to a different set of residuals. In fact, $\tilde{\mathbf{u}}_{it}$ defined by equation 6 is not the same as $\hat{\mathbf{u}}_{it}$ in equation 4, unless the weights used in the first stage at each time t are the same as in the second stage, namely, if $\mathbf{W}_{i,\tau(t-1)} = \mathbf{W}_i^0$ for all t. This condition can only occur when the weights used in the first stage are fixed and match the weights used in the second stage, which is not the case in our application. Thus, in general, the $\tilde{\mathbf{u}}_{it}$ matrices might be contemporaneously as well as serially correlated, even if the residuals of the fitted model in equation 4 are not.

To quantify the uncertainty around the point estimates of the generalized impulse response functions (GIRFs), we use a nonparametric bootstrap procedure, which requires an estimate of the covariance matrix of the stacked country-specific residuals, $\mathbf{u}_t = (\tilde{\mathbf{u}}_{0t}', \tilde{\mathbf{u}}_{1t}', \ldots, \tilde{\mathbf{u}}_{Nt}')'$, $\Sigma_{\tilde{u}}$. One possible estimate is the sample moment matrix,

22. See appendix B for a more detailed discussion and derivation of the solution to the GVAR with a given weight matrix.

$$\hat{\boldsymbol{\Sigma}}_{\tilde{u}} = \frac{\sum_{t=2}^{T-1} \tilde{\mathbf{u}}_t \tilde{\mathbf{u}}_t'}{(T-1)}.$$

In our application, however, where the dimension of the endogenous variables in the GVAR model (k) is larger than the time series dimension (T), $\Sigma_{\tilde{u}}$ is not guaranteed to be a positive definite matrix. This is an important consideration when computing bootstrapped error bands for the impulse responses or bootstrapped critical values for the structural stability tests. To avoid this problem, we use a shrinkage estimator of the covariance matrix in the empirical analysis, as explained in appendix B.[23]

Third, interdependence among countries in the GVAR model arises through many different channels. Direct trade linkages are only one of the important channels. The different country variables are also connected through the dependence of $\mathbf{x}_{it}$ on global variables, $\mathbf{d}_t$, and through the contemporaneous interdependence of shocks in country i on shocks in country j, as summarized by the estimated cross-country covariance, Σ_{ij}, where $\boldsymbol{\Sigma}_{ij} = Cov(\mathbf{u}_{it}, \mathbf{u}_{jt}) = E(\mathbf{u}_{it}\mathbf{u}_{jt}')$ for $i \neq j$. Unless we coherently link the country-specific models, as in the second step of the modeling strategy explained above, impulse responses of shocks to domestic and foreign variables cannot take account of the second- and higher-order interaction in the global system. Consequently, altering the direct trade linkages between country i and country j by altering the respective coefficient in the link matrix above does not necessarily change the bilateral interdependence between the two countries.

Finally, the shocks we consider in the paper are not identified, unlike what is claimed in the structural VAR literature.[24] We focus instead on shocks that could be triggered by different fundamental sources of disturbances, such as productivity, monetary policy, or other structural shocks, without attempting to identify the ultimate source of the disturbance. Distinguishing between the different factors that contribute to a particular variable change often involves incredible identifying assumptions. For instance, researchers are still debating the identification of a U.S. technology shock in a closed economy model. Such issues become even more vexing in a global model, and this paper thus

23. Dees and others (2010).

24. In principle, traditional impulse responses to orthogonalized shocks could also be computed, but they would depend on the specific identification scheme adopted. For instance, in the case of the typically used Cholesky scheme, the results would depend on the ordering of the variables and countries in the model, while GIRFs are invariant to such orderings.

does not try to identify the effects of a U.S. (or China) technology shock from all the other sources of disturbances that could prevail in the global economy.[25]

To investigate the transmission of shocks to the country-specific variables, we use GIRFs to take into account the possibility that the error terms of the GVAR are contemporaneously correlated across variables and countries.[26] For instance, a country-specific GDP shock can ultimately be stemming from a shift in demand or supply of output in that country, in other countries, or globally. GIRFs for such a shock show how changes in a given variable (say, U.S. GDP) or in a linear combination of changes in a number of variables (say, global output) affect the other variables in the GVAR on impact (first-round effects) and over time (second- and higher-order effects), regardless of the source of the change. As noted above, GIRFs do not answer the deeper question of whether such changes originate from technology shocks, monetary policy shocks, oil shocks, or other structural shocks. Instead, they describe what happens if there are changes to the errors, $\mathbf{u}_{it}$, of the conditional model, (equation 1), without trying to identify the sources of the changes. Unlike the errors in the standard VAR models, the shocks in the conditional models that comprise the GVAR are only weakly cross-sectionally correlated, which lends further support to the use of GIRFs for the analysis of the transmission of shocks across countries. The evidence on cross-country correlation of the errors of the country-specific VARX* model is given in appendix C.

A GVAR Model for Latin America in the World Economy

In this section, we discuss the model specification and report test results to check the validity of the weak exogeneity assumption of country-specific foreign variables and the stability of the parameters.

Model Specification

The GVAR model that we specify includes twenty-six country-specific VARX* models. We consider all major advanced and emerging economies in the world, accounting for about 90 percent of world GDP. Data availability limits us to five Latin American economies: Argentina, Brazil, Chile, Peru,

25. See Dees and others (2010) for an attempt to do so in a GVAR version of the canonical (three-equation) new Keynesian model.

26. GIRFs are developed in Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998).

TABLE 3. Variable Specification of the Country-Specific VARX* Models[a]

Non-U.S. models		U.S. model	
Domestic	*Foreign*	*Domestic*	*Foreign*
y_{it}	y^*_{it}	y_{US}	y^*_{US}
p_{it}	p^*_{it}	p_{US}	p^*_{US}
q_{it}	q^*_{it}	q_{US}	—
π_{it}	π^*_{it}	π_{US}	π^*_{US}
ρ^L_{it}	ρ^{L*}_{it}	ρ^L_{US}	—
—	—	—	$e^*_{US}-p^*_{US}$
$e^*_{it}-p^*_{it}$	p^0	p^0	—

a. In the non-U.S. models, the inclusion of the listed variables depends on data availability.

and Mexico. The euro area bloc is made up of the eight largest economies, and we include six countries for emerging Asia. Thus, the version of the GVAR model that we specify uses data for 33 countries.[27] The models are estimated over the period 1979:2 to 2009:4, thus including both the great recession of 2008–09 and the first two quarters of the recent global recovery.

With the exception of the U.S. model, all country models include the same set of variables, where available (see table 3). The variables included in each country model are real GDP (y_{it}), the inflation rate ($\pi_{it} = p_{it} - p_{i,t-1}$), the real exchange rate defined as ($e_{it} - p_{it}$), and, when available, real equity prices (q_{it}), a short interest rate (ρ^S_{it}), and a long interest rate (ρ^L_{it}), with $y_{it} = \ln(\mathrm{GDP}_{it}/\mathrm{CPI}_{it})$, $p_{it} = \ln(\mathrm{CPI}_{it})$, $q_{it} = \ln(\mathrm{EQ}_{it}/\mathrm{CPI}_{it})$, $e_{it} = \ln(E_{it})$, $\rho^S_{it} = 0.25 \cdot \ln(1 + R^S_{it}/100)$, and $\rho^L_{it} = 0.25 \cdot \ln(1 + R^L_{it}/100)$, where GDP_{it} is nominal gross domestic product of country i at time t (in domestic currency); CPI_{it} is the consumer price index in country i at time t (equal to 100 in year 2000); EQ_{it} is a nominal equity price index; E_{it} is the nominal exchange rate of country i at time t in terms of U.S. dollars; R^S_{it} is the short interest rate in percent per year (typically a three-month rate); and R^L_{it} is a long interest rate in percent per year (typically a ten-year rate). All country models (except the United States) also include the log of nominal oil prices (p^o_t) as a weakly exogenous foreign variable.

The U.S. model is specified differently. First, the oil price is included as an endogenous variable. In addition, given the importance of U.S. financial variables in the global economy, the U.S.-specific foreign financial variables, $q^*_{US,t}$ and $\rho^{*L}_{US,t}$, are not included in the U.S. model (see below for a discussion of the results of the weak exogeneity test applied to these variables). The real value of the U.S. dollar, by construction, is determined outside the U.S. model, and

27. For a full list of the countries included in the sample, see appendix A.

the U.S.-specific real exchange rate (defined as $e^*_{US,t} - p^*_{US,t}$) is included in the U.S. model as a weakly exogenous foreign variable.

Country-Specific Estimates and Tests

Given the importance of the weak exogeneity assumption in the construction of the GVAR model, together with the parameter stability for the counterfactual simulation exercise that we conduct in the paper, we focus on the evidence on these two sets of test statistics in our discussion.[28]

As noted above, for all countries, we treat the foreign variables as weakly exogenous. To test for the weak exogeneity of country-specific foreign variables and oil prices, the individual country models are first estimated under the null hypothesis that foreign variables are indeed weakly exogenous. The resultant error correction terms are then included in the auxiliary equations for country-specific foreign variables, and their statistical significance is tested jointly. Under the null hypothesis that foreign variables are weakly exogenous, the error correction terms must not be statistically significant.[29]

We find that the weak exogeneity hypothesis could not be rejected for the majority of variables considered, especially for core economies such as the United States, the euro area, and China. Specifically, only 10 out of the 156 exogeneity tests performed result in rejection of the weak exogeneity hypothesis. Not surprisingly, given the region's relative size and role in the world economy, almost all foreign variables in the Latin American models can be treated as weakly exogenous. Only foreign output in the model for Mexico and oil prices in the model for Brazil cannot be considered as weakly exogenous according to the test statistics reported. Such results can also arise by chance, however: given that we use a 5 percent significance level, we would expect at least 5 percent of the 130 tests performed to fail (that is, six or seven) even if the weak exogeneity hypothesis were valid in all cases. China also meets the weak exogeneity assumption despite its greatly increased importance in the world economy. While China's growth rate implies that at some point in the future it will cease to be "small" in terms of economic modeling, our test results suggest that at present China can still be viewed as a small open

28. The statistical assumptions made to specify the GVAR model are reported in detail in appendix C, together with a description of the impact multipliers and average pairwise correlations for all variables and countries included in the model. Appendix C also reports evidence on unit root tests, lag order selection, and the cointegration rank for all country models.

29. The details of the testing procedure and the results for the weak exogeneity test are presented in appendix C (see table C6 for results).

economy for the purpose of estimating the model parameters. This does not mean, however, that its increased weight in the world economy does not matter when we analyze the transmission of shocks emanating from its economy.

For the United States, the null hypothesis of weak exogeneity can be rejected for U.S.-specific foreign equity prices at the 5 percent level of significance, due to the prominence of U.S. equity markets in the global context. The weak exogeneity of U.S.-specific foreign long-run interest rates, however, cannot be rejected at the 5 percent level. Given the size and importance of U.S. equity and bond markets in international financial markets, we decided to exclude foreign long-run interest rates and foreign equity prices from the U.S. model. The foreign counterparts of output, inflation, and the real exchange rate (defined above) pass the weak exogeneity test and are therefore included in the U.S. model. The U.S.-specific foreign short-term interest rate, $\rho^{*S}_{US,t}$, also passes the weak exogeneity test and is included as a weakly exogenous variable in the U.S. model.[30]

The possibility of structural breaks is of particular concern in the case of emerging countries, which have been subject to significant political, social, and structural changes during our sample period. The GVAR implicitly accommodates co-breaking, which implies that the VARX* models that make up the GVAR are more robust to the possibility of structural breaks than standard VAR models or single equation models.[31] Focusing on Latin American real GDP variables, in particular, structural breaks are found in years when these countries were subject to severe shocks that coincide with the start and end of the hyperinflation periods in Brazil and Peru. While acknowledging that this evidence is problematic, we follow earlier GVAR work and provide bootstrap means and confidence bounds for the point estimates, which do allow for breaks in the error variance-covariances.[32]

Transmission of Shocks before and after China's Rise in the World Economy

To quantify the change in the transmission of external shocks to Latin America before and after the acceleration of the globalization process at the beginning of the 1990s and the emergence of China as a significant trading

30. This contrasts with Dees and others (2007).

31. Mizon and Hendry (1998).

32. Pesaran, Schuermann, and Weiner (2004); Dees and others (2007). See appendix C for a detailed account of parameter stability tests.

nation, we conduct a set of counterfactual simulation exercises along the lines discussed earlier. Specifically, while keeping constant the parameters of the VARX* models estimated in the first step of the GVAR methodology (with foreign variables constructed using time-varying trade weights), we solve the GVAR model in the second step with four different sets of trade matrices, based on fixed trade weights for the years 1985, 1995, 2005, and 2009. We then compare the resultant time profiles of the transmission of specific GDP shocks across different counterfactual trade linkages.

By focusing on these four sets of trade weights, we can quantify how changed geographical trade patterns may have altered the impact and transmission of shocks to Latin America and the world economy, abstracting from any implied changes to parameter estimates that might have taken place as a result of changing trade weights. Trade weights were relatively stable from 1985 to 1995 and then started to change steadily. Therefore, we expect the most marked changes to be associated with the weights in 1995 and 2009. We include the trade weights in 1985 and 2005 to get a better sense of the time-evolution of the estimated impacts and provide some evidence on the robustness of the results.

Our GVAR model has 134 variables (all endogenously determined), and there are numerous potentially relevant shocks that could be considered.[33] We consider two country-specific shocks with potential global impacts—namely, a Chinese GDP shock and a U.S. GDP shock—and investigate how their effects on the GDP of selected countries in the GVAR model change using alternative trade matrices. While the Chinese GDP shock is the main focus of our application, we look at a shock to U.S. GDP because it provides a natural benchmark against which to contrast the results for China. We focus on GDP shocks because they are of particular interest in light of the recent global crisis. We also consider a Latin American GDP shock and a GDP shock to the rest of emerging Asia (excluding India) because they shed light on the ongoing debate on the decoupling of emerging markets' business cycles from those of advanced economies. In the analysis of the international transmission of these shocks, we look at both regional and country-specific responses. The regional responses are constructed as weighted averages of the country-specific responses, using weights based on the purchasing power parity (PPP)

33. A full set of GIRFs for the baseline model is not reported but is available from the authors on request. In appendix C, we report a full set of impact multipliers that represent one summary dimension of the international linkages in the GVAR.

valuation of country GDP, which provide good measures of relative sizes of the economies under consideration.

As we noted earlier, we do not attempt to interpret these GDP shocks structurally, for instance, distinguishing between demand and supply sources of output change in the analysis.[34] In the GVAR model, once $\mathbf{x}_{it}$ is conditioned on $\mathbf{x}^*_{it}$, the estimated country-specific shocks have effectively little or no correlation across countries.[35] Thus, country-specific GDP shocks, conditional on rest-of-the-world GDP variables (which are present in every country model considered), have little or no cross-country correlations, although they are not orthogonal. This makes it possible to consider GIRFs to U.S. or Chinese GDP shocks with few concerns about reverse spillover effects from one country to the other. Nonetheless, we find that contemporaneous correlation of the shocks *within* country models remains sizable even after conditioning on global variables, thus precluding a structural interpretation of these country GDP shocks as supply or demand shocks, for example, without further a priori restrictions.

With these preliminary considerations in mind, the rest of this section reports and discusses the results of the counterfactual simulations. We report the point estimates of the GIRFs in the main text in figures 3 to 7, while the bootstrap error band results are reported in figures C2 to C9 in appendix C.

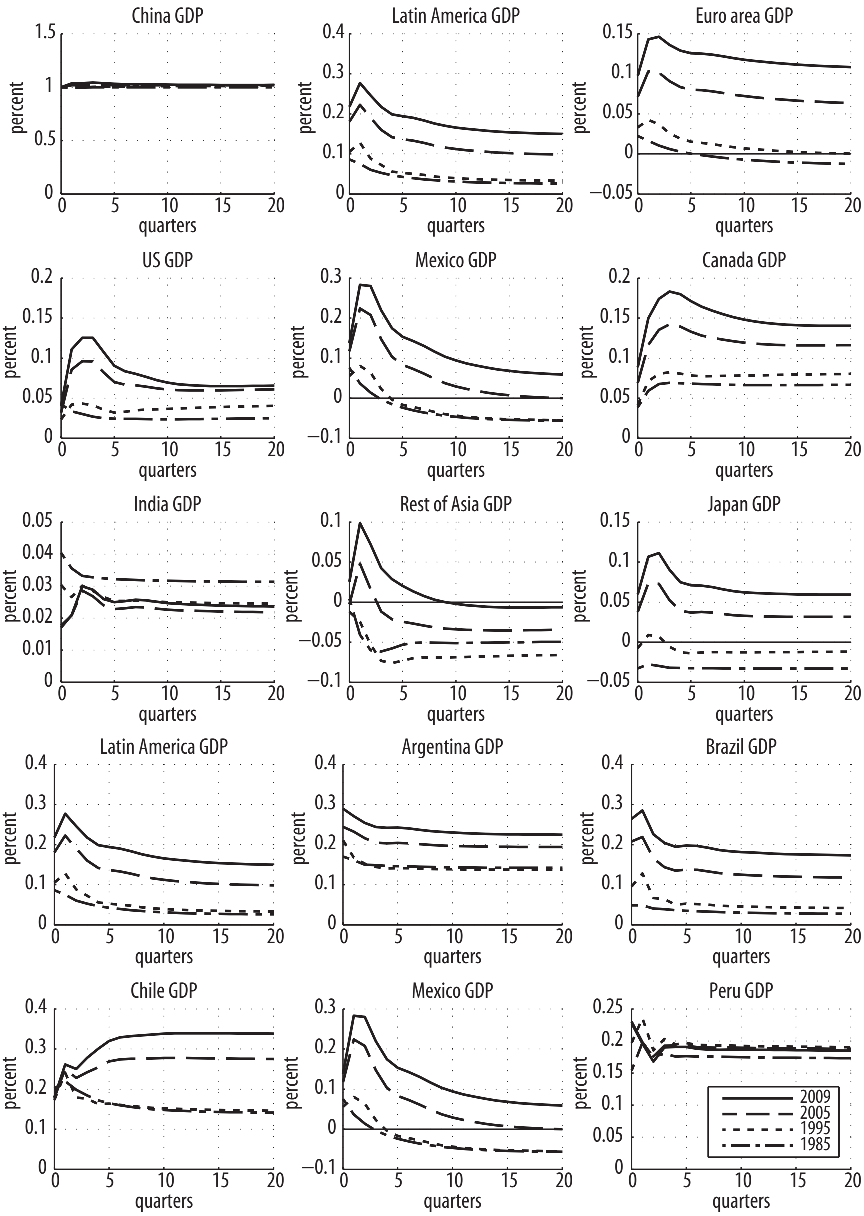
A Chinese GDP Shock

Figure 3 presents the GIRFs for a one percent increase in Chinese GDP, using 2009, 2005, 1995, and 1985 trade weights. In the Latin American region as a whole, the long-run response to this shock with 2009 weights is almost three times as large as the response associated with 1995 weights. The responses of all individual Latin American countries are qualitatively similar, but there are quantitative differences across countries in the region. The long-run responses of Chile and Brazil increase the most (almost four times), while those of Mexico and Peru increase the least. However, even the changes in the short-run response of Mexican GDP are sizable (reaching almost 0.3 percent as with the other Latin American countries in 2009), despite the much larger importance of NAFTA trade in Mexico's total trade. This is because

34. This contrasts with the approach of Dees and others (2010).

35. See tables C10 and C11 in appendix C for a detailed account of the average pairwise error correlations in the country-specific models of the GVAR.

FIGURE 3. GIRFs for a One Percent Increase in Chinese GDP[a]



a. Point Estimates for 1985, 1995, 2005, and 2009.

a Chinese GDP shock affects both the United States and Canada much more strongly with 2009 weights, which generates an indirect effect on Mexico. In contrast, it is puzzling that the strength of the impact and transmission of the shock does not increase in the case of a commodity exporter like Peru, despite the fact that its trade shares have evolved similarly to the other Latin American countries in the sample (see figure 1).

With more recent trade weights (2005 and 2009 weights), a Chinese GDP shock matters much more for both advanced and emerging economies, especially in the long run. For instance, the long-run impact of the shock on the United States with 2009 weights is about 50 percent stronger than with 1995 weights and about 100 percent stronger than in 1985. For the euro area and Canada, the changes in the transmission of a Chinese GDP shock with 2005 and 2009 weights are even more marked than in the United States. The increase in the impact is less pronounced in the case of Japan, but the rest of emerging Asia exhibits the same pattern of progressively increasing responses to a Chinese GDP shock when using more recent weights that the rest of the world displays. Only India, whose trade integration with the rest of the world is mainly driven by trade in services (which is not accounted for in the available trade statistics that we use to compute trade linkages), seems to be affected relatively less by a Chinese GDP shock with more recent trade weights. Moreover, differences between 2009 and 1985 responses to a Chinese GDP shock are not only quantitatively sizable but also statistically significant in the sense that in most cases, the 95 percent error bands for the bootstrapped 2009 responses do not contain zero values. In contrast, the effects are not statistically different from zero if we consider the 1985 trade weights.[36]

The reported changes in the transmission of the Chinese GDP shock to Latin America and the rest of the world are likely to have played an important role in the unfolding of the recent global financial and economic crisis. For instance, Cova, Pisani, and Rebucci estimate that absent the large fiscal stimulus enacted by China during the global crisis, China's GDP would be 2.6 percentage points lower in 2009.[37] The estimated elasticities to a Chinese GDP change reported in figure 3 imply that U.S. GDP growth would have been a quarter percentage point lower in 2009, and Latin American GDP

36. See figures C2 and C3 in appendix C for the bootstrapped impulse responses. The point estimates, which do not need to coincide with the mean of the bootstrapped distribution, are based on a one percent shock to GDP, while the bootstrapped distributions are based on a one standard deviation shock to GDP.

37. Cova, Pisani, and Rebucci (2010).

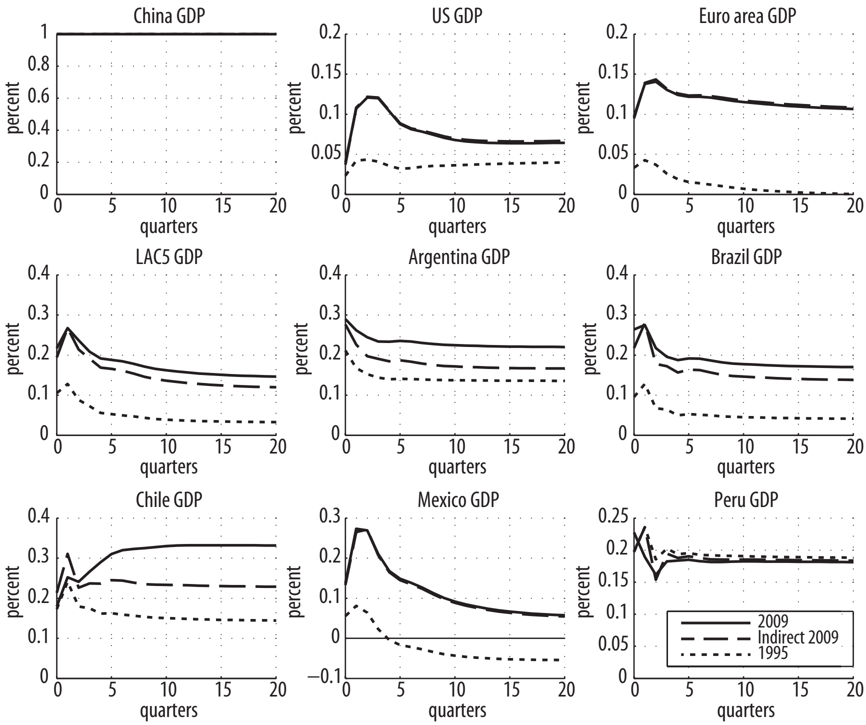
growth would have been almost a full percentage point lower.[38] Conversely, suppose that Chinese growth slowed in the medium to long term to about 7 percent a year, as currently forecasted in China's twelfth official five-year plan. This would shave almost half a percentage point from Latin America's long-term growth—probably more than 10 percent of the region's growth potential—with much larger short-term effects.[39] These effects are quite sizable, especially considering that these back-of-the-envelope calculations do not account for any likely associated financial market overreaction to such important changes in the fundamental driver of the region's business cycle.

In light of Mexico's responses to a Chinese GDP shock and, more generally, the stylized facts discussed in earlier sections, we questioned whether the increased impact of a Chinese GDP shock on other Latin American countries is due to direct or indirect trade linkages. That is, we set out to quantify whether the stronger impact of China on Latin America is more due to stronger bilateral trade ties between China and the region or to stronger indirect effects emanating from China's impact on the region's traditional and largest trading partners, namely, the United States and the euro area. To separate out these two effects, we conducted an additional counterfactual simulation, taking the 2009 trade matrix and changing China's weights in the total trade of the Latin American economies, with the exception of Mexico, to 1995 levels (thus resetting the direct trade links between the region and China to the 1995 level). All other entries in the link matrix were initially kept at their 2009 values, thus leaving the indirect links via the United States and the euro area unchanged. The difference between China's 1995 and 2009 weights in the total trade of each of the four Latin American countries was then redistributed proportionally to the remaining countries excluding the United States and the euro area, which were left unchanged at their 2009 levels. In this experiment, we also left Mexico's direct trade link with China unchanged at its 2009 level, because otherwise the response of the United States to the Chinese

38. With 2009 trade weights, the peak impacts of a Chinese GDP shock on U.S. GDP and Latin American GDP are 0.12 percent and 0.3 percent, respectively.

39. We conduct the following calculations: if China's growth rate falls by 3 percentage points to 7 percent a year, and given an estimated long-run elasticity of a Chinese GDP shock on Latin American GDP of about 0.15, the contraction implies a fall in Latin American GDP growth of around 0.4–0.5 percentage point in the long run. Assuming that Latin America's long-run growth rate is between 4 and 5 percent a year (as in the case of Brazil), a reduction of GDP growth by 0.4–0.5 percentage point represents a decline in potential growth of approximately 10 percent.

FIGURE 4. GIRFs for a One Percent Increase in Chinese GDP: Total and Indirect Effects[a]



a. Point estimates for 2009 and 1995; indirect effects for 2009.

GDP shock with this hybrid link matrix would change due to Mexico's large trade share in U.S. total trade, and the exercise would overstate the effects on Mexico.[40]

The results are reported in figure 4 and show that the indirect linkages are likely to be more important than the direct linkages, thus highlighting the strength of the general equilibrium dynamics that the GVAR modeling strategy captures. Muting the change in the direct trade link between China and Latin America (excluding Mexico) has no consequences on the United

40. In fact, Mexico had a 14 percent share of total trade of the United States in 2009, according to the IMF's Direction of Trade Statistics.

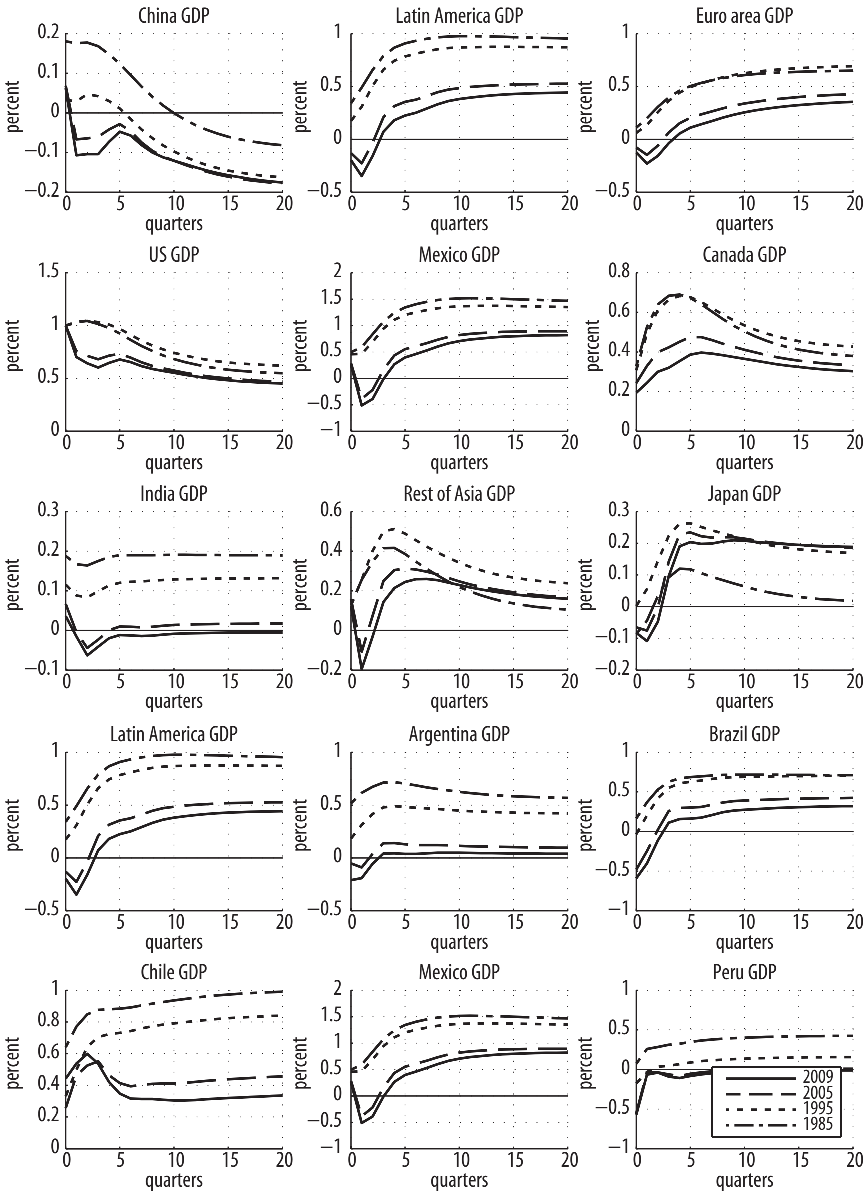
States, the euro area, or Mexico itself by construction. This is because Latin America excluding Mexico (whose trade shares are kept constant) is too small in trade terms to affect the United States. In the cases of Argentina, Brazil, and Chile, the changes in the impact of the Chinese GDP shock due to changed indirect linkages are at least as large as those due to changes in the direct links: changed indirect linkages explain at least half of the total change in the transmission of the shock (almost all of the change in the case of Brazil). In the case of Peru, there is a very small total change, so the distinction is immaterial. We interpret this evidence as suggesting that both direct and indirect effects contribute to the stronger impact of a Chinese GDP shock on the four Latin American countries, but the indirect transmission channel is at least as important as the more obvious direct links. In some cases, like Brazil, the indirect effects seem to be even more important than the direct effects.

This is clear evidence that the changed trade linkages between China, Latin America, and the rest of the world are affecting the region not only via stronger direct trade linkages (boosted by a persistent increase in commodity prices, which inflates the Latin American trade shares) but also through stronger ties between China and the region's traditional trading partners. An important implication of this result is that other countries in the broader Latin American region, such as countries in Central America and the Caribbean, might now be more affected by China via the increased impact of a Chinese GDP shock on the United States and the euro area. This result also suggests that the increased impact of a Chinese GDP shock on Mexico discussed above can be interpreted as a result of stronger indirect trade linkages between China and the other NAFTA member countries.

A U.S. GDP Shock

Figure 5 presents the GIRFs for a one percent increase in U.S. GDP. The impact of a U.S. GDP shock on advanced and emerging market economies falls considerably with more recent trade weights, especially in the short term, mirroring the shift in the geographical distribution of trade discussed earlier. Specifically, the impact of the shock on the United States itself with 2009 weights is almost half the size with 1995 weights in the first few quarters, and it is about 20–25 percent weaker over the longer term. The results for Canada are similar. In the case of the euro area the transmission of the shock weakens more uniformly across the horizon of the GIRF. The bootstrapped impulse responses to this shock suggest that these differences are not only quantitatively sizable but also statistically significant (see figures C4 and C5 in appendix C).

FIGURE 5. GIRFs for a One Percent Increase in US GDP[a]



a. Point Estimates for 1985, 1995, 2005, and 2009.

In the case of Latin America, the short-term impact of this shock falls dramatically with 2009 weights (becoming statistically insignificant), while the long-run impact is half that using 1995 weights. As in the case of the Chinese GDP shock, there are quantitative differences in responses of individual Latin American countries, but the qualitative pattern is common across all five economies. The long-run responses of Chile decrease the most, by almost half compared with 1995 trade weights. The reduction in the response is smallest for Mexico, though it is still sizable; this is to be expected given Mexico's membership in NAFTA.

The changes in the impact of the U.S. GDP shock on Asia are more mixed. The long-run impact on Chinese GDP falls dramatically with 2009 weights compared with the estimates using 1985 weights. However, these differences are significant only for the first two quarters. Japan and the rest of emerging Asia (driven by Korea, which is not reported separately) show some differences in the short-run effects, but the evidence does not imply a reduction in the impact of a U.S. GDP shock on these economies in the long run. Moreover, the bootstrapped responses show that these changes are not statistically significant.

These results imply that the effect of the recent U.S. great recession on Latin America would have been much more severe if this event had taken place in the mid-1990s. For instance, Izquierdo and Talvi estimate that the level of U.S. GDP at the peak of the recession was more than 7 percent below its potential.[41] If the crisis had taken place in the mid-1990s rather than the late 2000s, our simulations show that Latin America could have experienced the same output gap as the United States based on these estimates.[42] While good initial conditions at the beginning of the crisis and prompt international financial support have helped the region cope well with the recent global crisis, less dependency on the country at the epicenter of the crisis (the United States) has proved to be fortunate for the economic performance of the region.

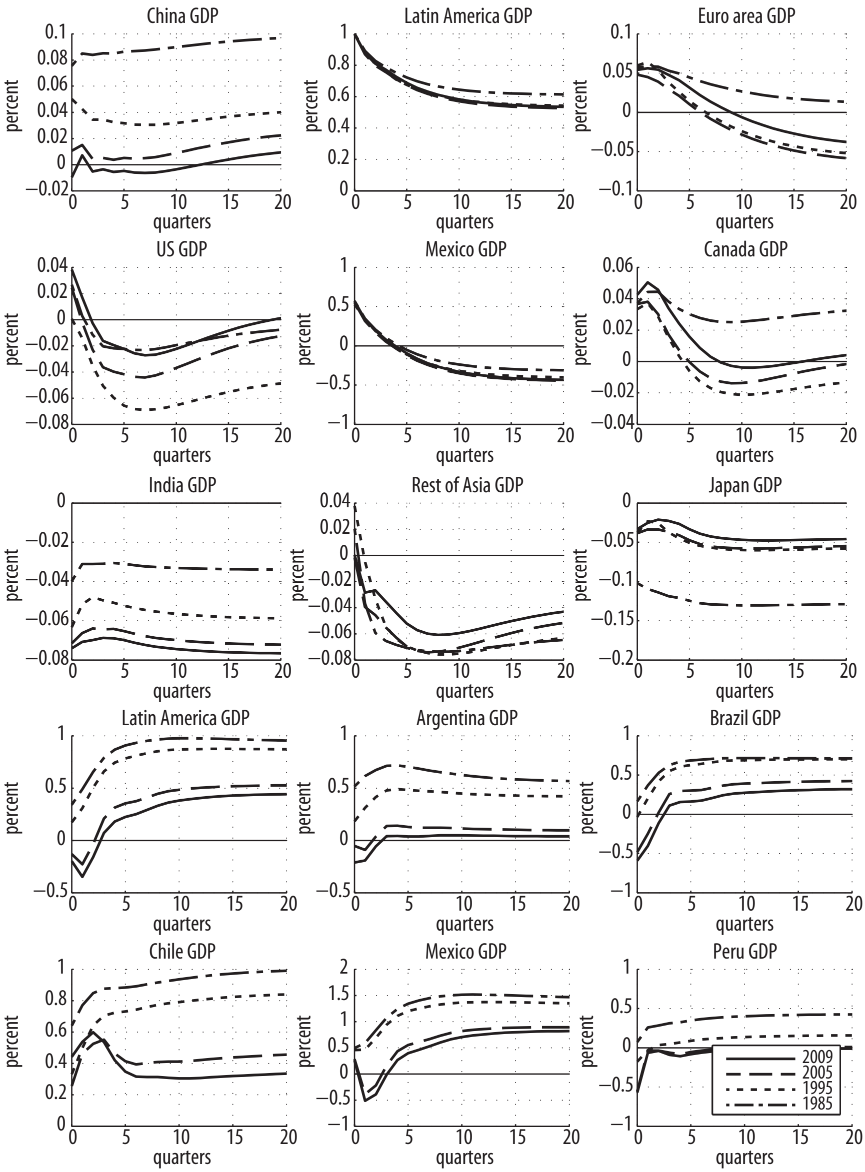
A GDP Shock in Latin America and the Rest of Emerging Asia

Consider now a one percent increase in Latin American GDP and in the GDP of emerging Asia excluding China and India. Figures 6 and 7 display the

41. Izquierdo and Talvi (2011).

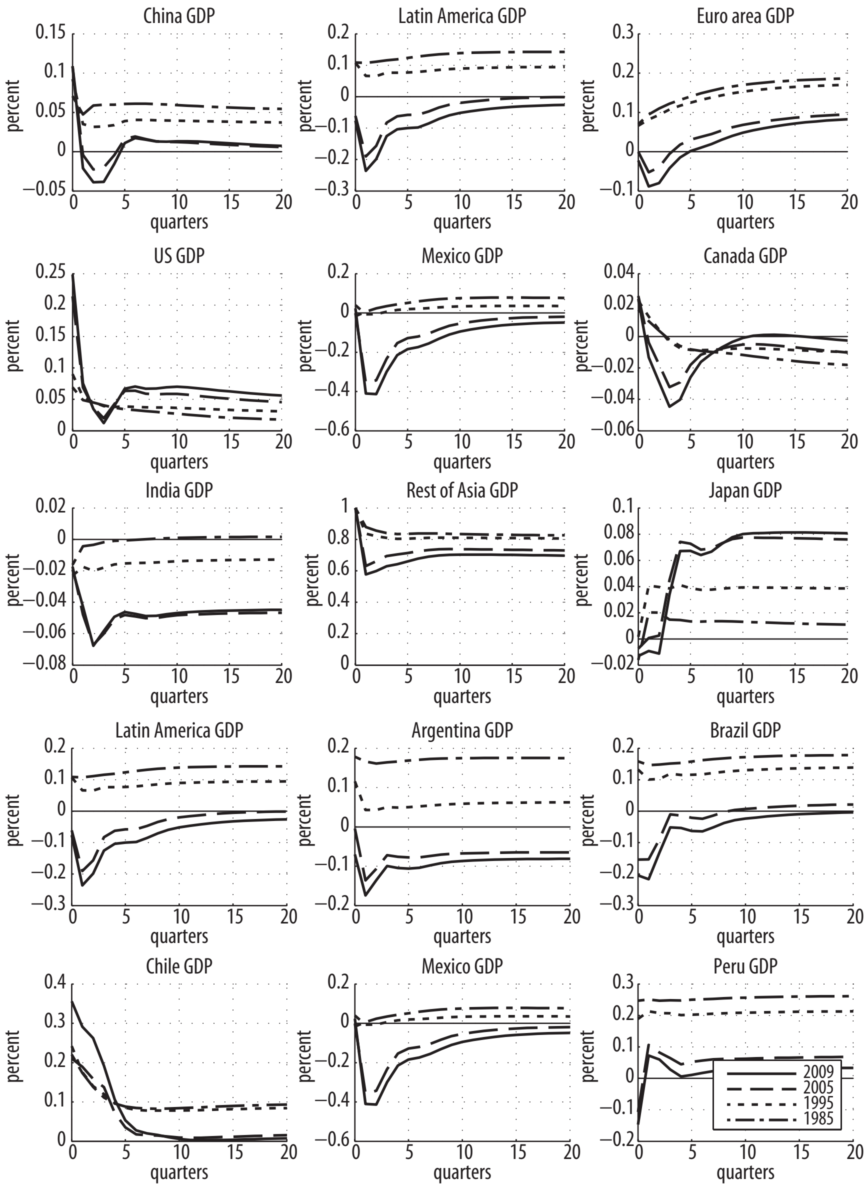
42. The long-run impact of a positive shock of a 1 percent rise in U.S. GDP on Latin American output is about 1 percent with 1995 weights, but only about 0.4 percent with 2009 weights.

FIGURE 6. GIRFs for a One Percent Increase in Latin American GDP[a]



a. Point Estimates for 1985, 1995, 2005, and 2009.

FIGURE 7. GIRFs for a One Percent Increase in Rest of Asia GDP[a]



a. Point Estimates for 1985, 1995, 2005, and 2009.

point estimates of the GIRFs for these two regions. These shocks are constructed as the weighted average (PPP-GDP average) of shocks to GDP in all Latin American and emerging Asian countries in the model, respectively.[43] As the figures show, the effects of these shocks with 2009 trade weights have remained virtually unchanged in the case of Latin America, and they have weakened slightly in the case of the emerging Asian economies. The reason is that these shocks have negligible effects on the largest economies of the world. For instance, with 2009 weights, a one percent increase in Latin American GDP, on impact, has no effects on Chinese and Japanese GDP, and its effects on the euro area is half the impact of the Chinese GDP shock discussed before. The Latin American shock has an impact on U.S. GDP that is similar to that of a Chinese GDP shock, but the impact of the Latin American shock (mostly through Mexico) dies out in two quarters, while the shock to Chinese GDP has a hump-shaped response, peaking above 0.1 percent within three to four quarters.

The bootstrapped GIRFs confirm that the transmission of these shocks to the rest of the world is not statistically significant with 2009 trade weights.[44] In contrast, with 1985 weights a Latin American GDP shock has a widespread, if short-lived, impact on the rest of the world. In the case of a GDP shock to emerging Asia, the transmission to the rest of the world is not statistically significant even with 1985 weights.

These results are pertinent to the much-debated decoupling hypothesis. According to this hypothesis, emerging markets have decoupled from advanced economies in recent years, in the sense that their growth dynamics have become more autonomous.[45] As a result, emerging markets as a group are starting to be an autonomous source of world growth. Our results, taken together with those on the transmission of a Chinese GDP shock, show that Latin America and the rest of emerging Asia (excluding China and India) are still too small to have a meaningful impact on the world economy. They cannot, as yet, be counted as an autonomous source of world growth, like China.

Our findings also suggest that Latin America and the rest of emerging Asia remain a collection of small open economies whose fluctuations can

43. The list of countries in the rest of emerging Asia is in appendix A.

44. See figures C6 to C9 for the bootstrapped impulse responses to a Latin American GDP shock and a GDP shock to emerging Asia.

45. See Kose and Prasad (2010) for an example of the decoupling hypothesis.

be affected strongly by the international business cycle. The key change we document is that their cycle is now more exposed to China and less exposed to the United States than in the past (although the impact of a U.S. GDP shock remains sizable). This impact occurs not only directly via stronger bilateral trade ties, but also, and perhaps more importantly, indirectly via China's stronger ties with advanced economies. In other words, the evidence reported in this paper suggests that the decoupling of emerging markets from advanced economies found in the existing literature is more likely related to the emergence of China as an important source of world growth, as opposed to a widespread decoupling of emerging market business cycles from cycles in advanced economies.

Conclusions

In this paper we investigated how China's emergence in the world economy has affected the international transmission of business cycles to five large Latin American economies. Using a GVAR model for the twenty-six largest advanced and emerging economies in the world, estimated with quarterly data from 1979:2 to 2009:4 and time-varying trade weights, we conducted a series of counterfactual exercises with different sets of trade weights for 1985, 1995, 2005, and 2009.

We found that the long-run impact of a Chinese GDP shock on the typical Latin American economy has increased three times since the mid-1990s. In contrast, and consistent with previous findings, the long-run effect of a U.S. GDP shock has halved over the same period, with even sharper declines in the short-term impact. We show that the larger impacts of a Chinese GDP shock owe as much to indirect effects, associated with stronger trade linkages between China and Latin America's largest trading partners (namely, the United States and the euro area), as to direct effects stemming from tighter trade linkages between China and Latin America, boosted by the decade-long boom in commodity prices that has inflated trade shares. The results also suggest that the transmission of domestic shocks originating in Latin America and the rest of emerging Asia (excluding China and India) has not changed much over the same period.

These findings help to explain why the five Latin American economies we consider recovered much faster than initially anticipated from the recent global crisis. In fact, the evidence shows that Latin America's growth was mostly driven by a fast-growing economy that enacted a powerful fiscal stimulus during the global crisis, with a relatively smaller push from the economy that was at the epicenter of the crisis. Had the trade linkages been those prevailing in the mid-1990s, the region would have likely suffered a much sharper downturn than it actually experienced. This evidence also suggests that the decoupling found in the existing literature might be related to the emergence of China as an important source of world growth, as opposed to a more general tendency of emerging markets' business cycles to diverge from those of advanced economies.

These same findings expose new vulnerabilities for Latin America and the rest of the world economy. Latin America remains a small open economy vulnerable to external shocks, without the necessary weight to affect the international business cycle with its own growth dynamics. Latin America and the rest of the world economy, including the region's traditional and still largest trading partners, now rely relatively more on China and less on the United States relative to only fifteen years ago. China is a large, low-middle-income economy whose transition to high-income economy will continue for many years to come. China is also relatively less stable than the United States.[46] While the changes documented here have had positive, stabilizing effects on the Latin America business cycle during the recent global crisis, the same facts may predict negative, destabilizing effects if and when China's growth begins to slow. Thus, going forward, Latin America and the rest of the world are likely to become more volatile.

Appendix A: Data Sources and Data Treatment

Our GVAR model uses data for thirty-three countries. The core economies included in the model are China, Japan, the United Kingdom, and the United States. Data availability limits us to five Latin American economies: Argentina, Brazil, Chile, Peru, and Mexico. The euro area block is made up of the eight largest economies: Austria, Belgium, Finland, France, Germany, Italy,

46. In fact, the average conditional standard deviation of a Chinese GDP shock in the first stage of the GVAR analysis is more than twice as large as that of the United States.

the Netherlands, and Spain.[1] Other developed and European economies in the model are Australia, Canada, New Zealand, Norway, Sweden, and Switzerland. For emerging Asia, we have Indonesia, Korea, Malaysia, the Philippines, Singapore, and Thailand. Finally, the model also considers India, South Africa, Saudi Arabia, and Turkey.

This version of the GVAR data set revises and extends up to 2009:4 the data set used in Pesaran, Schuermann, and Smith, which covers the period 1979:1–2006:4.[2] Data were collected in June 2010, and we refer to the updated data set as the 2009 vintage.

Real GDP

To compile the 2009 vintage real GDP, we used the IMF's International Financial Statistics (IFS) database and the Inter-American Development Bank's Latin Macro Watch (LMW) database.[3] Countries are divided into three groups: those for which quarterly and seasonally adjusted data are available; those for which quarterly data are available, but not seasonally adjusted; and those for which only annual data are available. For the first group, we used the IFS 99BVRZF series (GDP VOL) for Australia, Canada, France, Germany, Italy, Japan, the Netherlands, New Zealand, South Africa, Spain, Switzerland, the United Kingdom, and the United States. We extrapolated the Pesaran-Schuermann-Smith data set using quarterly growth rates of the IFS series from 2004:1 to 2009:4.

For the second group, we used the IFS 99BVPZF series (GDP VOL) for Austria, Belgium, Finland, India, Indonesia, Korea, Malaysia, Norway, Singapore, Sweden, Thailand, and Turkey. These series were seasonally adjusted using Eviews, applying the National Bureau's X12 program.[4] As in the first group, the data set was extended with forward extrapolation of Pesaran-Schuermann-Smith data, using quarterly growth rates of the adjusted IFS series from 2004:1 to 2009:4.

1. The time series data for the euro area are constructed as weighted averages using purchasing power parity (PPP) GDP weights, averaged over 2006–08 (source: World Bank, World Development Indicators database).

2. Pesaran, Schuermann, and Smith (2009b). That data set is, in turn, an extension of the data set used in Pesaran, Schuermann, and Smith (2009a), which covers the period 1979:1–2005:4.

3. For further information, see www.iadb.org/Research/LatinMacroWatch/lmw.cfm.

4. Seasonal adjustment was performed on the log difference of GDP using the additive option. Then, using the first observation of the unadjusted log GDP series, we accumulate the adjusted log changes. Finally, we obtained seasonally adjusted level series by taking the exponential function of the log-adjusted series.

A variety of methods was used for the third group. For Saudi Arabia, the annual seasonally unadjusted IFS BVPZF GDP VOL series was interpolated to obtain the quarterly values.[5] This series was then treated as the quarterly seasonally unadjusted data. For the Philippines, the quarterly rate of change of a seasonally adjusted real GDP index (source: Bloomberg, ticker PHNAGDPS Index) was used to extrapolate forward Pesaran-Schuermann-Smith data from 2004:1 to 2009:4.

For the Latin American countries—namely, Argentina, Brazil, Chile, Mexico, and Peru—the IDB LMW data were used (series: GDP, Real Index s.a.), and the series were updated in the same manner as described for quarterly seasonally adjusted data.

For China, Pesaran, Schuermann, and Smith interpolate quarterly GDP from IFS annual data, as for Saudi Arabia.[6] Given the increasing importance of China in the world economy, the construction of a quarterly real GDP index from national sources may provide some value added. As no institution publishes a quarterly real GDP index for China, it has to be compiled from a nominal GDP series. The National Bureau of Statistics (NBS) of China releases quarterly nominal GDP series without seasonal adjustments.[7] Accordingly, we constructed a quarterly real GDP index for China as follows. First, we seasonally adjusted the nominal GDP from NBS (using the procedure described below). Then, we used the following formula:

$$\log(RGDP_1) = \log\left(\frac{GDP_1}{CPI_1}\right), \text{ for } t = 1;$$

$$\log(RGDP_t) = \log(RGDP_{t-1}) + \log\left(\frac{GDP_t}{GDP_{t-1}}\right) - \log\left(\frac{CPI_t}{CPI_{t-1}}\right), \text{ for } t \geq 2;$$

where CPI is defined in the next subsection. The series displays noisy features in the first part of the sample and starts to show more plausible patterns from 1994:1 onward, providing a natural cut-off date. Therefore, we used the new series from 1994:1 to 2009:4 and extrapolated backward to 1979:1 using the quarterly rate of change of the China GDP series in Pesaran, Schuermann, and Smith.[8]

5. The interpolation procedure is described in supplement A of Dees and others (2007).

6. Pesaran, Schuermann, and Smith (2009b).

7. The NBS series can be accessed from Datastream, ticker: CH GDP (DS CALCULATED) CURN.

8. Pesaran, Schuermann, and Smith (2009b). The Chinese GDP series is subject to major data revisions. We therefore updated the nominal Chinese GDP series in April 2011 (after the most recent data revision) and used the updated series to construct our real GDP measure.

Consumer Price Index

To create the 2009 vintage CPI, we collected the IFS CPI 64zf (level) series for all countries except China. For countries that do not need seasonal adjustment, the quarterly growth rates of these series were used to extrapolate forward the Pesaran-Schuermann-Smith data from 2001:1 to 2009:4. Consistent with the procedure below in the subsection on seasonality, the CPI series for the following countries were seasonally adjusted: Austria, Belgium, Canada, Chile, Finland, France, Germany, India, Italy, Japan, Korea, Mexico, the Netherlands, New Zealand, South Africa, Spain, Sweden, Switzerland, Thailand, the United Kingdom, and the United States.[9] The quarterly rate of change of the adjusted IFS series was used to extrapolate forward the Pesaran-Schuermann-Smith data from 2000:1 to 2009:4, to obtain the 2009 vintage CPI.

For China, we used Datastream data (source: National Bureau of Statistics, ticker CHCONPR%F; year-on-year rate of change, NSA). The Datastream rate of change was used to create a series in levels, which was then seasonally adjusted using Eviews, applying the National Bureau's X12 program.[10] The 2009 vintage CPI for China was obtained by forward extrapolation of the Pesaran-Schuermann-Smith data set using the rate of change of the adjusted Datastream series from 2000:1 to 2009:4.

Equity Price Index

Updated equity price series are from Bloomberg, while the Pesaran-Schuermann-Smith data set uses Datastream. We took a quarterly average of the MSCI Country Index in local currency for each of the following countries: Argentina, Australia, Austria, Belgium, Canada, Chile, Finland, France, Germany, India, Italy, Japan, Korea, the Netherlands, Norway, New Zealand, the Philippines, South Africa, Spain, Sweden, Switzerland, Thailand, the United Kingdom, and the United States.[11] For Malaysia, the MSCI Index is not available, so we took a quarterly average of the local composite

9. Seasonal adjustment was performed with Eviews, using the X12 program with the additive option.

10. We used the same procedure here as for real GDP.

11. To construct an MSCI Country Index, every listed security in the market is identified. Securities are free-float adjusted, classified in accordance with the Global Industry Classification Standard (GICS), and screened by size, liquidity, and minimum free float (www.mscibarra.com).

index from Datastream (ticker KLPCOMP; local currency). The quarterly average was computed based on the closing price on the last Wednesday of each month. That is, we used the last Wednesday of each month and then took a simple average of these Wednesday prices for the first three months of the year to obtain our first quarterly price index. We then took the average of the Wednesday values for the next three months to get the second quarterly price index, and so on. Finally, the 2009 vintage equity price index was obtained by forward extrapolation of the Pesaran-Schuermann-Smith data using the rate of change of the new series from 2004:1 to 2009:4.

Exchange Rates

Exchange rate series are from Bloomberg. We took a quarterly average of the nominal bilateral exchange rates vis-à-vis the U.S. dollar (units of foreign currency per U.S. dollar) for each country.[12] The quarterly average was computed based on the closing value on the last Wednesday of each month, as described for the equity price index. The 2009 vintage exchange rate was obtained by forward extrapolation of the Pesaran-Schuermann-Smith data set using the rate of change of the new series from 2004:1 to 2009:4.

The exchange rate series for the euro economies refer to the pre-euro exchange rates (that is, national currencies to the dollar). To denominate them in euros, we took the quarterly average of the euro exchange rate vis-à-vis the U.S. dollar (source: Bloomberg, ticker EUR Curncy). We then used the 1999:1 value of this series as the base and extrapolated it backward and forward using the rate of change of the series denominated in national currencies.

Short-Term Interest Rates

IFS is the main source of data for short-term interest rates. Consistent with Pesaran-Schuermann-Smith, the IFS deposit rate (60Lzf series) is used for Argentina, Chile, China, and Turkey. The IFS discount rate (60zf series) is

12. The list of Bloomberg tickers is as follows: ARS JPMQ Curncy, AUD BGN Curncy, ATS CMPN Curncy, BEF CMPN Curncy, BRL BGN Curncy, CAD BGN Curncy, CNY BGN Curncy, CLP BGN Curncy, COP BGN Curncy, FIM CMPN Curncy, FRF CMPN Curncy, DEM BGN Curncy, INR CMPN Curncy, IDR BGN Curncy, ITL BGN Curncy, JPY BGN Curncy, KRW BGN Curncy, MYR BGN Curncy, MXN BGN Curncy, NLG CMPN Curncy, NOK BGN Curncy, NZD BGN Curncy, PEN BGN Curncy, PHP BGN Curncy, ZAR BGN Curncy, SAR BGN Curncy, SGD BGN Curncy, ESP CMPN Curncy, SEK BGN Curncy, CHF BGN Curncy, THB BGN Curncy, TRY BGN Curncy, GBP BGN Curncy, and VEF BGN Curncy.

used for New Zealand and Peru. The IFS Treasury bill rate (60Czf series) is used for Canada, Malaysia, Mexico, the Philippines, South Africa, Sweden, the United Kingdom, and the United States. The IFS money market rate (60Bzf series) is used for Australia, Brazil, Finland, Germany, Indonesia, Italy, Japan, Korea, Norway, Singapore, Spain, Switzerland, and Thailand. For Austria, Belgium, France, and the Netherlands no data are available for any of these series from 1999:1, when the euro was introduced. We used the country-specific IFS money market rate (60Bzf series) from 1979:1 to 1998:4 and completed the series to 2009:4 using the corresponding data (60Bzf series) for Germany as the representative euro area interest rate.

For India, quarterly averages of daily Bloomberg data on India three-month Treasury bill yield (ticker GINTB3MO Index) are constructed in the same way as the quarterly exchange rate series.[13] When IFS data were not available, gaps were filled using Bloomberg data: Norway in 2007:1 and 2009:4 (ticker NKDRC CMPN Curncy), the Philippines from 2008:4 to 2009:1 (ticker PH91AVG Index), and Sweden from 2009:2 to 2009:4 (ticker GSGT3M Index). The Pesaran-Schuermann-Smith data series are extended with these series from 2004:1 to 2009:4.

Long-Term Interest Rates

We use the IFS government bond yield (61zf series) to extend data for all eighteen countries for which long-term interest rate data are available, namely, Australia, Austria, Belgium, Canada, France, Germany, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, South Africa, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The Pesaran-Schuermann-Smith data series are extended with these series from 2004:1 to 2009:4.

Oil Price Index

For the oil price, we used a Brent crude oil price from Bloomberg (series: current pipeline export quality Brent blend, ticker CO1 Comdty). To construct the quarterly series, we took the average of daily closing prices for all trading days in the quarter. The quarterly rate of change of this new series was used to extrapolate forward the Pesaran-Schuermann-Smith data set from 2004:1 to 2009:4.

13. This is an indicative Treasury bill rate polled daily by Bloomberg from various sources. The constructed series is not exactly equal to the original DdPS series, but it is very close (correlation of 99.63 percent).

PPP-GDP Weights

The main source for the country-specific GDP weights is the World Bank's World Development Indicator (WDI) database. The GDP in purchasing power parity terms in current international dollars (ticker NY.GDP.MKTP.PP.CD) was downloaded for all countries from 2006 to 2008.

Trade Matrices

To construct the trade matrices, we used the IMF Direction of Trade Statistics. For all the countries considered, we downloaded the import-export matrix (using CIF prices) with annual frequency. The data for 2009 exports and imports are appended to the original Pesaran-Schuermann-Smith data set. We use trade matrices for 1979–2009 for estimation in our paper.

Assessing the Joint Significance of Seasonal Effects

To assess the joint significance of the seasonal components of the real output and inflation series, we used the following procedure:

—Let $S1$, $S2$, $S3$, and $S4$ be the usual seasonal dummies, such that Si, $i = 1, 2, 3, 4$, takes the value of one in the *ith* quarter and zero in the other three quarters.

—Construct $S14 = S1 - S4$, $S24 = S2 - S4$, and $S34 = S3 - S4$.

—Run a regression of Δy (where the lower case stands for the natural logarithm of the corresponding variable) on an intercept and $S14$; $S24$; $S34$. Denote the ordinary least squares (OLS) estimates of $S14$, $S24$, and $S34$ by $a1$, $a2$, and $a3$.

—Asses the joint significance of the seasonal components by testing the null hypothesis that $a1 = a2 = a3 = 0$, using the F statistic.

—If the null hypothesis is rejected at the 10 percent level, perform seasonal adjustment on the log difference of the original series using the X-12 procedure described below.

Method of Seasonality Adjustment

To seasonally adjust the log(GDP) series, which is assumed to be an $I(1)$ process, we first seasonally adjust $\Delta\log(\text{GDP})$ using the X-12 quarterly seasonal adjustment method in Eviews with the additive option, to obtain $\Delta\log(\text{GDP})_{SA}$. We then use the first observation of raw series log(GDP) (in levels, not seasonally adjusted) and the seasonally adjusted series of the changes, $\Delta\log(\text{GDP})_{SA}$, to obtain the seasonally adjusted level series $\log(\text{GDP})_{SA}$.

To update seasonally adjusted series 2009:4, and assuming we have the seasonally adjusted series from 1979:1 to 2006:4, we download the raw series, for example from 2000:1 to 2009:4, and seasonally adjust with the procedure described above. We then use the seasonally adjusted new series in growth rates to update the original seasonally adjusted series. To avoid possible abrupt changes in the updated series, we also overwrite two years of the original series for all variables except inflation. In the case of inflation, we overwrite six years of original series, to accommodate major data revisions in the series. Specifically, we update all series (except inflation) from 2004:1 to 2009:4 and the inflation series from 2000:1 to 2009:4.

Appendix B: GVAR Solution and Bootstrapping

This appendix presents a detailed derivation of the solution of the GVAR with a given weight matrix and shows that the estimated country-specific models (from the first step) can be stacked and solved for any given trade weights, which we denote by $\mathbf{W}_i^0$. We also denote $\mathbf{W}_{NT}$ to be the set of all weight matrices, which we use to estimate the country-specific models in the first step,

$$\mathbf{W}_{NT} = \left\{\mathbf{W}_{it}, i = 0, 1, \ldots, N; t = 1, 2, \ldots, T\right\}.$$

Then, the country-specific estimates of the VARX* in equation 4 can be denoted by $\hat{\mathbf{\Phi}}_i(\mathbf{W}_{NT})$, $\hat{\mathbf{\Lambda}}_{i0}(\mathbf{W}_{NT})$, and $\hat{\mathbf{\Lambda}}_{i1}(\mathbf{W}_{NT})$ and the associated residuals by $\hat{\mathbf{u}}_{it}(\mathbf{W}_{NT})$. Also, let $\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}) = \{Vec[\hat{\mathbf{\Phi}}_i(\mathbf{W}_{NT})]', Vec[\hat{\mathbf{\Lambda}}_{i0}(\mathbf{W}_{NT})]', Vec[\hat{\mathbf{\Lambda}}_{i1}(\mathbf{W}_{NT})]'\}'$, and use the $k_i \times k$ selection matrix $\mathbf{S}_i$, such that

$$\mathbf{x}_{it} = \mathbf{S}_i \mathbf{x}_i.$$

Then

$$\begin{aligned}
\mathbf{S}_i\mathbf{x}_t &= \hat{\mathbf{\Phi}}_i\left(\mathbf{W}_{NT}\right)\mathbf{S}_i\mathbf{x}_{t-1} + \hat{\mathbf{\Lambda}}_{i0}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0\mathbf{x}_t + \hat{\mathbf{\Lambda}}_{i1}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0\mathbf{x}_{t-1} + \tilde{\mathbf{u}}_{it}, \\
\left[\mathbf{S}_i - \hat{\mathbf{\Lambda}}_{i0}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0\right]\mathbf{x}_t &= \left[\hat{\mathbf{\Phi}}_i\left(\mathbf{W}_{NT}\right)\mathbf{S}_i + \hat{\mathbf{\Lambda}}_{i1}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0\right]\mathbf{x}_{t-1} + \tilde{\mathbf{u}}_{it} \\
\mathbf{G}_i\left(\hat{\boldsymbol{\theta}}_i\left(\mathbf{W}_{NT}\right)\right)\mathbf{x}_t &= \mathbf{H}_i\left(\hat{\boldsymbol{\theta}}_i\left(\mathbf{W}_{NT}\right)\right)\mathbf{x}_{t-1} + \tilde{\mathbf{u}}_{it},
\end{aligned} \tag{B1}$$

where

$$\mathbf{G}_i\left(\hat{\boldsymbol{\theta}}_i\left(\mathbf{W}_{NT}\right), \mathbf{W}_i^0\right) = \mathbf{S}_i - \hat{\mathbf{\Lambda}}_{i0}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0 \tag{B2}$$

and

$$\text{(B3)} \qquad \mathbf{H}_i\left(\hat{\boldsymbol{\theta}}_i\left(\mathbf{W}_{NT}\right), \mathbf{W}_i^0\right) = \hat{\boldsymbol{\Phi}}_i\left(\mathbf{W}_{NT}\right)\mathbf{S}_i + \hat{\boldsymbol{\Lambda}}_{i1}\left(\mathbf{W}_{NT}\right)\mathbf{W}_i^0.$$

Note that $\tilde{\mathbf{u}}_{it}$ will not be the same as $\hat{\mathbf{u}}_{it}(\mathbf{W}_{NT})$, unless at time t we have $\mathbf{W}_{i,\tau(t-1)} = \mathbf{W}_i^0$, which can only occur when the weights are fixed. Stacking equation B1 for $i = 0, 1, \ldots N,$ we have

$$\mathbf{G}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\mathbf{x}_t = \mathbf{H}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\mathbf{x}_{t-1} + \tilde{\mathbf{u}}_t,$$

where

$$\begin{aligned}
\mathbf{G}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right) &= \Big(\mathbf{G}_0'\left(\hat{\boldsymbol{\theta}}_0\left(\mathbf{W}_{NT}\right), \mathbf{W}_0^0\right), \mathbf{G}_1'\left(\hat{\boldsymbol{\theta}}_1\left(\mathbf{W}_{NT}, \mathbf{W}_1^0\right)\right), \ldots \\
&\qquad \mathbf{G}_N'\left(\hat{\boldsymbol{\theta}}_N\left(\mathbf{W}_{NT}, \mathbf{W}_N^0\right)\right)\Big)', \\
\mathbf{H}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right) &= \Big(\mathbf{H}_0'\left(\hat{\boldsymbol{\theta}}_0\left(\mathbf{W}_{NT}\right), \mathbf{W}_0^0\right), \mathbf{H}_1'\left(\hat{\boldsymbol{\theta}}_1\left(\mathbf{W}_{NT}\right), \mathbf{W}_1^0\right), \ldots \\
&\qquad \mathbf{H}_N'\left(\hat{\boldsymbol{\theta}}_N\left(\mathbf{W}_{NT}, \mathbf{W}_N^0\right)\right)\Big)', \\
\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right) &= \left(\hat{\boldsymbol{\theta}}_0'\left(\mathbf{W}_{NT}\right), \hat{\boldsymbol{\theta}}_1'\left(\mathbf{W}_{NT}\right), \ldots \hat{\boldsymbol{\theta}}_N'\left(\mathbf{W}_{NT}\right)\right)', \\
\mathbf{W}^0 &= \left(\mathbf{W}_0^0, \mathbf{W}_1^0, \ldots, \mathbf{W}_N^0\right).
\end{aligned}$$

Therefore,

$$\text{(B4)} \qquad \mathbf{x}_t = \mathbf{F}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\mathbf{x}_{t-1} + \mathbf{G}^{-1}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\tilde{\mathbf{u}}_t,$$

where

$$\text{(B5)} \qquad \mathbf{F}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right) = \mathbf{G}^{-1}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\mathbf{H}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right).$$

If we abstract from parameter uncertainty and take the value of $\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT})$ as given and true, then n-step-ahead forecasts are given by

$$E\left(\mathbf{x}_{t+n} \middle| \mathbf{I}_{t-1}\right) = \left[\mathbf{F}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\right]^{n+1}\mathbf{x}_{t-1}.$$

Similarly, the n-step-ahead generalized impulse response of the effect of a unit shock to $\xi_t = \mathbf{a}'\mathbf{u}_t$ on the composite variable $q_t = \mathbf{b}'\mathbf{x}_t$, where $\mathbf{a}$ and $\mathbf{b}$ are $k \times 1$ selection vectors, is given by

$$\text{(B6)} \qquad g_q\left(n, \sigma_\xi\right) = \frac{\mathbf{b}'\left[\mathbf{F}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\right]^n \mathbf{G}^{-1}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\Sigma_{\tilde{u}}\mathbf{a}}{\sqrt{\mathbf{a}'\Sigma_{\tilde{u}}\mathbf{a}}},$$

where $\sigma_\xi = \sqrt{\mathbf{a}'\Sigma_{\tilde{u}}\mathbf{a}}$ is the size of the unit shock to ξ_t. The error covariance matrix can be estimated using the residuals $\tilde{\mathbf{u}}_{it}$ defined by equation B1. One possible estimate is the sample moment matrix, $\hat{\Sigma}_{\tilde{u}} = \left(T-1\right)^{-1} \sum_{t=2}^{T-1} \tilde{\mathbf{u}}_t \tilde{\mathbf{u}}_t'$, where $\tilde{\mathbf{u}}_t = (\tilde{\mathbf{u}}_{0t}', \tilde{\mathbf{u}}_{1t}', \ldots, \tilde{\mathbf{u}}_{Nt}')'$. One could also use a shrinkage version of $\hat{\boldsymbol{\Sigma}}_{\tilde{u}}$. Since N is large relative to T, we use a shrinkage estimator of $\hat{\boldsymbol{\Sigma}}_{\tilde{u}}$ defined by

$$\text{(B7)} \qquad \tilde{\Sigma}_{\tilde{u}}\left(\lambda\right) = \lambda\hat{\Sigma}_{\tilde{u}} + \left(1 - \lambda\right) Diag\left(\hat{\Sigma}_{\tilde{u}}\right),$$

where λ is the shrinkage parameter and $Diag(\hat{\boldsymbol{\Sigma}}_{\tilde{u}})$ is a diagonal matrix formed from the diagonal elements of $\hat{\boldsymbol{\Sigma}}_{\tilde{u}}$.

Bootstrapping the GVAR Model with Time-Varying Weights

To derive the empirical distribution of the structural stability tests and of the impulse response functions, we use a nonparametric bootstrap procedure, which takes account of the sampling uncertainty associated with the estimates $\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT})$, for given values of $\mathbf{W}_{NT}$ and $\mathbf{W}^0$. In this case, the appropriate residuals for the purpose of drawing bootstrapped samples are $\tilde{\mathbf{u}}_{it}$, given by equation B1. This suggests generating the bootstrap samples, denoted by $\mathbf{x}_t^{(b)}$, $b = 1, 2, \ldots B$, according to the process

$$\text{(B8)} \qquad \mathbf{x}_t^{(b)} = \mathbf{F}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\mathbf{x}_{t-1}^{(b)} + \mathbf{G}^{-1}\left(\hat{\boldsymbol{\theta}}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\tilde{\mathbf{u}}_t^{(b)},$$

for $t = 1, 2, \ldots T$, where $\mathbf{F}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)$ given by equation B4, $\mathbf{x}_0^{(b)} = \mathbf{x}_0$ (or $\mathbf{x}_{-1}^{(b)} = \mathbf{x}_{-1}$ if a GVAR(2) is considered), and where $\mathbf{x}_0$ and $\mathbf{x}_{-1}$ are the realized initial data vectors. For each b, $\tilde{\mathbf{u}}_t^{(b)}$ is generated by random draws from $\tilde{\mathbf{u}}_t$, allowing for the fact that $\hat{\boldsymbol{\Sigma}}_{\tilde{u}}$ is nondiagonal and can be singular. This can be achieved using the Cholesky factor of $\hat{\boldsymbol{\Sigma}}_u$ (or a shrinkage version of it) along the lines proposed by Dees and others.[14]

14. See the supplement in Dees and others (2007).

To carry out the Cholesky factorization, the estimated error variance covariance matrix must be nonsingular, and we also use a shrinkage parameter defined by equation B7. In the applications reported in the paper, $\tilde{\mathbf{\Sigma}}_{\tilde{u}}(\lambda)$ becomes nonsingular for values of $\lambda \geq 0.8$, but to reduce the effects of the sampling errors in the Cholesky factorization of $\tilde{\mathbf{\Sigma}}_{\tilde{u}}(\lambda)$, we decided to set $\lambda \geq 0.5$, halfway between the sample estimate and its diagonal version. For consistency between the point estimates and the bootstrapped results, we also set $\lambda \geq 0.5$ for the point estimates. Finally, prior to any resampling, the residuals were recentered to ensure that their bootstrap population mean is zero.

For each bootstrap sample, *b,* the individual country models must be estimated with the same set of time-varying weights, $\mathbf{W}_{NT}$, lag orders, and cointegrating rank. Denote the parameter estimates based on the *bth* bootstrap sample by $\hat{\boldsymbol{\theta}}^{(b)}(\mathbf{W}_{NT})$. Then the associated impulse response functions across the different bootstrapped replications are given by

$$\text{(B9)}\quad g_q^{(b)}\left(h, \sigma_\xi\right) = \frac{\mathbf{b}'\left[\mathbf{F}\left(\hat{\boldsymbol{\theta}}^{(b)}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\right]^h \mathbf{G}^{-1}\left(\hat{\boldsymbol{\theta}}^{(b)}\left(\mathbf{W}_{NT}\right), \mathbf{W}^0\right)\tilde{\Sigma}_{\tilde{u}}^{(b)}\mathbf{a}}{\sqrt{\mathbf{a}'\tilde{\Sigma}_{\tilde{u}}^{(b)}\mathbf{a}}},$$

for $b = 1, 2, \ldots B$. The bootstrap confidence bounds can now be computed for each h using the percentiles of $g_q^{(b)}(h, \sigma_\xi)$, over $b = 1, 2, \ldots B$.

Appendix C: Additional Estimation Results and Bootstrapped GIRFs

In this section we present and discuss formal specification tests for key aspects of the model, namely, integration properties of the series, lag-length selection and cointegration rank, weak exogeneity of foreign variables, and parameter stability. In addition, we comment on some of the main estimation results, such as impact elasticities and pairwise cross-section correlation of variables and residuals. Finally, we present bootstrapped GIRFs, to complement the results on the point estimates in the main body of the paper.

Unit Root Tests

The GVAR model can be specified in terms of either stationary or integrated variables. Nonetheless, here we follow Dees and others and assume that the variables included in the country-specific models are integrated of order one, or $I(1)$.[15] This permits us to distinguish between short-run and long-run relations and interpret the long-run relations as cointegrating.

To examine the integration properties of both the domestic and foreign variables, we use unit root tests. Given the recognized poor performance of augmented Dickey-Fuller (ADF) tests in small samples, we consider unit root t statistics based on weighted symmetric (WS) estimation of ADF-type regressions introduced by Park and Fuller.[16] The lag length employed in the WS unit root tests is selected by the Akaike information criterion (AIC) based on standard ADF regressions.

Results of the WS statistics for the level, first differences, and second differences of the country-specific domestic and foreign variables are reported in tables C1 and C2. This battery of tests generally supports the unit root hypothesis, with only a few exceptions. First, the null hypothesis of unit root for Mexican GDP is rejected by the test. Nonetheless, this is a borderline case, and a more standard ADF test does not reject the unit root hypothesis. Second, the unit root hypothesis is also rejected for long-term interest rates in most advanced economies and for the real exchange rate in Mexico and the United Kingdom. For China, Switzerland, the United Kingdom, and some developing countries, the unit root hypothesis for inflation is rejected. On inflation, since overdifferencing is likely to be a less serious specification error than wrongly including an $I(2)$ variable, we opt for the inclusion of inflation as an $I(1)$ variable, as in Pesaran, Schuermann, and Weiner.[17] In fact, the order of integration is generally not a property of an economic variable, but a convenient statistical approximation to distinguish between the short-run, medium-run, and long-run variations in the data. With the adoption of a medium-run perspective, which is consistent with nonstationarity of most economic variables, treating inflation as a stationary variable is likely to invalidate the statistical analysis. For the remaining countries and variables, the test results generally support our working assumption that the variables included in the country-specific models can be treated as $I(1)$ variables.

15. Dees and others (2007).

16. Park and Fuller (1995). Dees and others (2007) argue that the weighted symmetric ADF tests exploit the time reversibility of stationary autoregressive processes in order to increase their power performance. Leybourne, Kim, and Newbold (2005) and Pantula, González-Farías, and Fuller (1994) provide evidence of the superior performance of the weighted symmetric ADF test in comparison with the standard ADF test of the ADF-GLS test proposed by Elliott, Rothenberg, and Stock (1996). See also chapter 4 of Microfit 5 Manual (Pesaran and Pesaran, 2009) for a detailed discussion.

17. Pesaran, Schuermann, and Weiner (2004).

TABLE C1. Unit Root Test Statistics for Domestic Variables[a]

Variable	*Crit. val.*	*Argentina*	*Australia*	*Brazil*	*Canada*	*Chile*	*China*	*Euro area*	*India*	*Indonesia*	*Japan*	*Korea*	*Malaysia*	*Mexico*
y (with trend)	−3.24	−1.29	−1.52	−1.50	−3.38	−1.49	−2.78	−1.39	−1.68	−2.33	−0.69	−1.44	−2.64	−3.41
y (no trend)	−2.55	2.04	1.91	1.66	1.47	1.99	1.62	1.54	1.65	2.07	1.55	0.77	1.48	1.50
Dy	−2.55	−4.92	−4.53	−4.48	−4.73	−3.86	−4.81	−4.41	−4.31	−4.59	−4.65	−3.65	−5.03	−4.89
DDy	−2.55	−8.88	−11.01	−6.87	−7.29	−10.78	−7.15	−7.00	−10.41	−10.68	−9.39	−11.97	−9.22	−7.28
Dp (with trend)	−3.24	−2.88	−2.78	−3.54	−2.02	−2.78	−3.61	−3.51	−2.89	−3.08	−3.74	−3.42	−2.69	−3.41
Dp (no trend)	−2.55	−2.62	−1.13	−2.47	−0.17	−2.23	−2.10	−2.17	−1.20	−1.41	−0.87	−2.05	−1.42	−1.11
DDp	−2.55	−5.93	−6.79	−11.67	−8.34	−7.97	−6.48	−9.12	−7.36	−6.71	−6.98	−6.57	−7.00	−10.86
DDDp	−2.55	−13.87	−8.91	−10.12	−9.31	−8.69	−8.65	−8.43	−9.58	−9.06	−9.09	−8.40	−9.51	−8.93
eq (with trend)	−3.24	−2.54	−2.58	−3.14	−1.95	−2.71	−2.68	−2.48	−2.35	−2.39	−2.67	−2.36	−2.69	−1.95
eq (no trend)	−2.55	−0.47	−1.03	−0.81	−0.60	−1.03	−0.94	−0.57	−0.74	−0.98	−0.70	−0.79	−0.97	−0.62
Deq	−2.55	−6.88	−7.00	−7.41	−6.43	−6.98	−7.04	−6.97	−6.94	−7.13	−7.03	−6.98	−7.08	−6.40
DDeq	−2.55	−9.80	−12.03	−12.98	−7.99	−12.61	−8.14	−9.67	−9.84	−9.56	−7.98	−9.88	−9.47	−7.99
ep (with trend)	−3.24	−2.03	−2.80	−1.85	−2.86	−3.01	−2.19	−3.43	−1.63	−1.74	−1.71	−2.16	−1.84	−2.42
ep (no trend)	−2.55	−1.40	−0.14	−0.61	−0.71	−2.12	−1.26	−0.19	−0.50	1.40	0.00	1.07	−0.08	−2.48
Dep	−2.55	−3.72	−5.08	−7.87	−4.32	−8.28	−3.97	−7.73	−7.34	−8.74	−4.84	−7.79	−6.66	−4.06
DDep	−2.55	−12.00	−7.69	−12.00	−7.23	−12.55	−14.65	−8.08	−8.17	−7.99	−12.24	−12.28	−7.75	−13.43
r (with trend)	−3.24	−2.73	−3.09	−3.19	−3.68	−2.44	−2.82	−2.15	−2.34	−2.93	−2.78	−2.76	−3.49	−3.60
r (no trend)	−2.55	−2.58	−1.28	−1.42	−1.28	−2.05	−1.58	−1.31	−1.08	−1.52	−1.10	−1.13	−1.63	−1.48
Dr	−2.55	−10.15	−5.20	−14.37	−3.80	−10.75	−5.82	−10.53	−6.93	−4.64	−6.26	−5.91	−4.49	−5.60
DDr	−2.55	−10.94	−8.78	−12.19	−9.97	−10.80	−10.57	−10.61	−11.21	−8.94	−9.97	−10.00	−8.63	−9.83
lr (with trend)	−3.24	−2.72	−3.61	−2.85	−3.96	−2.78	−3.20	−3.73	−2.76	−3.44	−3.13	−3.33	−2.72	−3.86
lr (no trend)	−2.55	−0.92	−0.67	−0.94	−1.14	−0.87	−1.21	−0.77	−0.82	−0.89	−0.88	−0.94	−0.79	−1.12
Dlr	−2.55	−5.56	−5.57	−5.51	−5.73	−5.56	−5.13	−5.76	−5.62	−5.17	−5.68	−5.26	−5.35	−5.56
DDlr	−2.55	−8.10	−8.53	−8.15	−7.83	−8.29	−8.48	−8.19	−8.18	−8.24	−8.08	−8.29	−8.09	−7.93

(*continued*)

TABLE C1. Unit Root Test Statistics for Domestic Variables[a] (*Continued*)

Variable	*Crit. val.*	*Norway*	*N.Zealand*	*Peru*	*Philippines*	*S.Arabia*	*S.Africa*	*Singapore*	*Sweden*	*Switzerland*	*Thailand*	*Turkey*	*U.K.*	*U.S.*
y (with trend)	−3.24	−3.02	−2.59	−1.69	−2.04	−2.27	−2.04	−2.46	−2.93	−2.59	−2.58	−2.59	−3.15	−1.78
y (no trend)	−2.55	0.63	0.70	1.94	0.99	0.79	0.53	1.77	1.33	1.07	1.71	1.43	1.43	1.56
Dy	−2.55	−4.30	−4.49	−4.61	−4.60	−4.38	−3.72	−4.96	−3.39	−4.56	−4.57	−4.42	−4.63	−4.26
DDy	−2.55	−7.38	−11.00	−10.67	−11.50	−11.80	−11.86	−7.26	−9.05	−8.49	−9.99	−7.16	−7.96	−9.84
Dp (with trend)	−3.24	−2.34	−2.47	−2.94	−3.14	−3.03	−3.40	−3.89	−2.47	−2.35	−2.68	−2.96	−2.32	−3.08
Dp (no trend)	−2.55	−0.63	−0.62	−2.39	−1.32	−1.87	−1.47	−1.03	−0.58	−0.50	−1.40	−1.65	−0.43	−1.01
DDp	−2.55	−6.71	−7.10	−9.14	−7.07	−7.22	−6.61	−7.57	−6.85	−7.00	−7.40	−6.61	−7.28	−9.58
DDDp	−2.55	−10.19	−9.24	−8.42	−8.70	−8.89	−8.50	−10.03	−8.33	−8.62	−9.12	−8.73	−8.64	−8.84
eq (with trend)	−3.24	−2.73	−2.85	−2.28	−2.29	−2.42	−2.41	−2.78	−2.56	−2.36	−2.60	−2.43	−2.64	−3.30
eq (no trend)	−2.55	−0.84	−0.85	−0.60	−0.97	−0.89	−0.87	−0.83	−0.82	−0.86	−0.87	−0.75	−0.73	−0.84
Deq	−2.55	−6.92	−6.94	−6.95	−6.98	−7.16	−7.20	−7.23	−6.96	−6.79	−7.07	−6.79	−6.96	−7.26
DDeq	−2.55	−12.74	−7.99	−12.33	−9.64	−7.90	−10.00	−9.59	−9.85	−9.91	−9.72	−9.96	−9.74	−8.12
ep (with trend)	−3.24	−2.40	−3.10	−2.23	−1.82	−3.30	−2.73	−1.54	−2.68	−2.54	−2.83	−2.60	−2.31	−2.09
ep (no trend)	−2.55	−0.10	−0.07	−1.08	0.51	−3.26	−1.82	−0.64	−0.17	−0.13	−1.67	−0.94	−0.13	1.01
Dep	−2.55	−6.86	−4.86	−4.43	−4.54	−3.82	−4.63	−4.67	−6.89	−6.81	−4.58	−7.28	−6.72	−7.11
DDep	−2.55	−8.17	−7.91	−13.06	−13.62	−7.21	−7.28	−12.18	−7.59	−9.96	−12.81	−7.71	−9.99	−7.67
r (with trend)	−3.24	−2.58	−3.18	−2.64	−2.75	−2.37	−2.47	−3.27	−2.39	−2.38	−2.57	−2.30	−2.30	−1.63
r (no trend)	−2.55	−1.00	−1.46	−2.14	−1.16	−1.56	−1.26	−1.45	−0.87	−0.97	−1.29	−1.04	−0.88	−1.01
Dr	−2.55	−5.09	−4.40	−11.58	−7.05	−8.95	−6.17	−4.98	−5.75	−5.45	−5.68	−9.04	−6.02	−11.46
DDr	−2.55	−8.76	−8.52	−10.43	−10.23	−9.13	−10.05	−7.45	−9.58	−9.78	−9.79	−9.75	−10.02	−11.21
lr (with trend)	−3.24	−2.72	−2.62	−3.80	−2.90	−2.80	−2.76	−2.68	−2.43	−2.52	−2.57	−2.53	−2.44	−3.23
lr (no trend)	−2.55	−0.64	−0.90	−0.91	−0.80	−0.77	−0.82	−0.82	−0.84	−0.88	−0.81	−0.91	−0.91	−0.93
Dlr	−2.55	−5.80	−5.52	−5.54	−5.48	−5.37	−5.45	−5.56	−5.61	−5.42	−5.28	−5.52	−5.58	−4.92
DDlr	−2.55	−8.32	−8.17	−8.19	−8.15	−8.17	−8.34	−8.15	−8.07	−7.78	−8.13	−8.20	−7.86	−8.47

a. Based on weighted symmetric ADF regressions. The WS statistics (Park and Fuller, 1995) for all level variables are based on regressions including a linear trend, except for the interest rate variables. The WS statistics for variables in first and second differences are based on regressions including an intercept and no linear trend. The 95 percent critical value of the WS statistics for regressions with trend is −3.24, and for regressions without trend −2.55.

TABLE C2. Unit Root Test Statistics for Foreign Variables[a]

Variable	*Crit. val.*	*Argentina*	*Australia*	*Brazil*	*Canada*	*Chile*	*China*	*Euro area*	*India*	*Indonesia*	*Japan*	*Korea*	*Malaysia*	*Mexico*
y (with trend)	−3.24	−2.20	−3.06	−2.39	−2.70	−2.40	−2.04	−1.18	−1.22	−1.80	−0.80	−1.10	−2.21	−3.34
y (no trend)	−2.55	−0.18	1.83	1.70	0.97	1.05	0.72	0.87	1.33	2.51	0.83	0.84	1.72	0.95
Dy	−2.55	−5.15	−6.47	−6.21	−4.92	−6.16	−3.54	−3.90	−7.92	−7.01	−3.94	−5.24	−5.45	−4.09
DDy	−2.55	−7.36	−9.10	−7.81	−7.31	−9.68	−11.19	−7.76	−10.44	−8.17	−7.19	−7.51	−7.94	−9.75
Dp (with trend)	−3.24	−3.70	−3.67	−2.71	−3.48	−5.06	−3.04	−2.01	−5.69	−5.84	−3.16	−2.86	−5.45	−3.80
Dp (no trend)	−2.55	−2.61	−2.42	−2.45	−1.21	−1.87	−3.02	−0.68	−5.39	−5.85	−1.53	−2.18	−5.11	−2.81
DDp	−2.55	−12.36	−9.80	−6.30	−7.61	−7.05	−6.85	−6.66	−9.00	−8.68	−7.57	−6.82	−8.91	−5.76
DDDp	−2.55	−14.91	−10.05	−8.86	−10.03	−11.03	−8.78	−8.89	−9.48	−8.68	−11.03	−8.46	−11.79	−14.88
eq (with trend)	−3.24	−3.26	−4.52	—	−2.86	−2.30	—	−2.45	−3.67	—	−1.85	−2.74	−3.02	—
eq (no trend)	−2.55	−2.77	−0.74	—	−0.76	−0.33	—	−0.93	−0.87	—	−1.67	−1.64	−1.90	—
Deq	−2.55	−6.76	−5.69	—	−6.21	−5.08	—	−6.76	−7.22	—	−5.06	−5.71	−6.15	—
DDeq	−2.55	−8.09	−8.34	—	−8.53	−7.43	—	−9.96	−9.16	—	−8.71	−13.13	−9.90	—
ep (with trend)	−3.24	−2.26	−2.62	−2.17	−1.78	−2.33	−1.25	−2.36	−1.22	−2.59	−2.05	−2.82	−2.20	−3.70
ep (no trend)	−2.55	−2.09	0.29	−1.00	1.14	−1.18	−1.23	−0.16	−0.26	−2.64	−0.30	−0.94	−0.87	−0.80
Dep	−2.55	−7.24	−7.88	−7.25	−7.46	−6.91	−7.08	−6.83	−5.65	−8.10	−5.24	−5.60	−7.25	−7.12
DDep	−2.55	−9.33	−9.18	−8.35	−7.70	−10.73	−10.80	−10.03	−12.13	−11.18	−7.47	−8.73	−8.91	−10.39
r (with trend)	−3.24	−2.71	−3.29	−2.79	−4.08	−5.00	−1.63	−3.04	−3.03	−4.10	−3.20	−2.59	−2.12	−2.03
r (no trend)	−2.55	−2.27	−1.95	−2.65	−1.17	−1.04	−1.43	−1.18	−2.70	−4.05	−1.80	−0.88	−1.99	−1.78
Dr	−2.55	−15.88	−7.47	−9.18	−5.86	−6.76	−6.13	−3.91	−6.66	−6.42	−4.94	−7.80	−6.87	−6.25
DDr	−2.55	−12.92	−11.01	−11.36	−9.28	−8.51	−7.90	−8.37	−8.59	−12.04	−5.33	−9.40	−8.58	−10.91
lr (with trend)	−3.24	—	−2.08	—	−3.54	—	—	−3.05	—	—	−2.50	−2.46	—	—
lr (no trend)	−2.55	—	−1.22	—	−1.28	—	—	−1.02	—	—	−0.85	−0.34	—	—
Dlr	−2.55	—	−5.64	—	−5.69	—	—	−5.14	—	—	−5.44	−6.73	—	—
DDlr	−2.55	—	−9.10	—	−8.58	—	—	−8.40	—	—	−7.99	−9.20	—	—

(*continued*)

TABLE C2. Unit Root Test Statistics for Foreign Variables[a] (*Continued*)

Variable	*Crit. val.*	*Norway*	*N.Zealand*	*Peru*	*Philippines*	*S.Arabia*	*S.Africa*	*Singapore*	*Sweden*	*Switzerland*	*Thailand*	*Turkey*	*U.K.*	*U.S.*
y (with trend)	−3.24	−1.80	−1.76	−1.46	−2.18	−0.56	−1.54	−1.49	−2.44	−2.67	−1.36	−2.73	−2.80	−2.45
y (no trend)	−2.55	2.51	1.41	0.59	0.46	0.58	1.26	1.68	0.65	1.50	1.29	1.47	−0.87	1.23
Dy	−2.55	−6.39	−6.53	−7.63	−3.56	−2.95	−5.05	−6.11	−4.51	−5.19	−3.09	−7.75	−2.97	−4.74
DDy	−2.55	−10.83	−9.33	−9.10	−9.94	−17.63	−7.87	−8.57	−8.03	−8.17	−9.40	−9.14	−12.69	−7.66
Dp (with trend)	−3.24	−4.75	−3.81	−3.35	−5.17	−4.47	−4.27	−3.78	−3.69	−4.67	−3.07	−2.25	−2.65	−1.34
Dp (no trend)	−2.55	−2.03	−2.40	−3.13	−4.40	−3.34	−2.80	−3.43	−2.06	−3.52	−2.50	−1.57	−1.41	0.04
DDp	−2.55	−7.86	−7.49	−7.99	−6.86	−8.79	−8.31	−9.86	−6.84	−10.67	−7.78	−7.84	−8.25	−8.64
DDDp	−2.55	−9.71	−9.35	−10.13	−8.72	−9.61	−9.11	−9.44	−8.42	−9.42	−8.71	−10.41	−10.39	−9.43
eq (with trend)	−3.24	−4.05	−2.38	—	−1.75	—	−4.59	−3.83	−2.92	−2.11	−1.79	—	−1.77	−1.75
eq (no trend)	−2.55	−0.97	−1.69	—	−1.46	—	−0.29	−1.80	−0.38	−0.65	−1.57	—	−0.75	−0.61
Deq	−2.55	−7.83	−6.16	—	−4.51	—	−8.42	−6.39	−6.86	−6.57	−5.02	—	−7.13	−6.24
DDeq	−2.55	−14.26	−13.18	—	−13.07	—	−7.44	−10.17	−12.60	−12.27	−10.34	—	−7.40	−8.02
ep (with trend)	−3.24	−2.66	−2.85	−1.80	−2.13	−1.97	−3.12	−1.44	−2.53	−2.49	−2.47	−1.35	−3.29	—
ep (no trend)	−2.55	0.04	−0.39	0.38	−0.24	−1.13	−2.00	1.49	−1.11	−0.15	−0.70	−0.37	−0.10	—
Dep	−2.55	−7.24	−6.55	−8.61	−6.00	−2.86	−4.79	−6.37	−6.99	−7.48	−5.55	−5.97	−5.59	—
DDep	−2.55	−8.37	−7.92	−8.68	−7.47	−11.04	−15.51	−8.30	−8.14	−10.06	−8.99	−9.97	−8.86	—
r (with trend)	−3.24	−2.91	−3.12	−3.39	−3.37	—	−2.89	−3.11	−2.28	−2.20	−3.69	−1.48	−3.35	−3.76
r (no trend)	−2.55	−1.57	−1.95	−3.18	−2.51	—	−2.84	−1.48	−1.29	−2.08	−2.11	−1.49	−1.18	−1.65
Dr	−2.55	−8.36	−8.15	−4.45	−7.94	—	−5.93	−4.57	−7.95	−4.93	−6.29	−9.08	−6.63	−3.70
DDr	−2.55	−8.53	−9.45	−8.94	−9.74	—	−8.14	−8.16	−10.61	−8.42	−7.85	−9.07	−8.83	−7.24
lr (with trend)	−3.24	−1.43	−2.02	—	—	—	−0.69	—	−3.51	−2.58	—	—	−3.03	−3.98
lr (no trend)	−2.55	−1.28	−0.96	—	—	—	−1.50	—	−0.70	−1.70	—	—	−0.43	−1.51
Dlr	−2.55	−7.08	−7.58	—	—	—	−8.38	—	−6.92	−5.91	—	—	−7.98	−5.83
DDlr	−2.55	−7.73	−9.09	—	—	—	−8.30	—	−8.04	−7.72	—	—	−8.60	−7.73

a. Based on weighted symmetric ADF regressions. The WS statistics (Park and Fuller, 1995) for all level variables are based on regressions including a linear trend, except for the interest rate variables. The WS statistics for variables in first and second differences are based on regressions including an intercept and no linear trend. The 95 percent critical value of the WS statistics for regressions with trend is −3.24, and for regressions without trend −2.55.

Selecting Lag Orders and Cointegration Ranks

We select lag orders and cointegration ranks of the country-specific cointegrating VARX* models under the assumptions that the included foreign variables are weakly exogenous and that the parameters of the individual models are stable over time. Evidence for these hypotheses is discussed in the next two subsections.

We select the lag orders, p_i and q_i, of the individual country VARX*(p_i, q_i) models according to the Akaike information criterion, under the constraints imposed by data limitations. Accordingly, the lag order of the foreign variables, q_i, is set equal to one in all countries; for the same reason, we set the constraint $p_i \leq 2$. In preliminary analysis of the GIRFs, we observed very ragged responses for Argentina, Brazil, Chile, India, Indonesia, New Zealand, Norway, Sweden, and Peru, and we changed the orders of the VARX* models for these countries from VARX*(2, 1) to VARX*(1, 1).

We then proceed with the cointegration analysis, in which the country-specific models are estimated subject to reduced rank restrictions.[18] To this end, the error correction forms of individual country equations are derived. The rank of the cointegrating space for each country was tested using Johansen's trace and maximal eigenvalue statistics as set out in Pesaran, Shin, and Smith for models with weakly exogenous $I(1)$ regressors, unrestricted intercepts, and restricted trend coefficients.[19]

The order of the VARX* models as well as the number of cointegration relationships are presented in table C3. Tables C4 and C5 report the trace test statistics and the 95 percent critical values for all the country-specific VARX* models, respectively.[20] We chose the trace test because it has better small sample properties compared to the maximal eigenvalue test.

To address the issue of possible overestimation of the number of cointegration relationships based on asymptotic critical values and to ensure the stability of the global model, we reduced the number of cointegration relations for a number of countries.[21] Specifically, we made the following adjustments in the number of cointegration relations based on the results implied by the statistical tests: Argentina from 3 to 1; Australia from 4 to 2; Canada from 3 to 1; Chile from 3 to 2; euro area from 2 to 1; India from 2 to 1; Indonesia from 2 to 1; Japan from 3 to 1; Korea from 5 to 1; Mexico from 3 to 2; New Zealand

18. Johansen (1992).
19. Pesaran, Shin, and Smith (2000).
20. The critical values are taken from MacKinnon (1991).
21. See, for example, Dees and others (2007).

TABLE C3. Lag Orders of the Country-Specific VARX* Models and the Number of Cointegrating Relations

Country	p_i	q_i	*CV*	*Country*	p_i	q_i	*CV*
China	1	1	1	Malaysia	1	1	1
Euro area	2	1	1	Philippines	2	1	1
Japan	2	1	1	Singapore	1	1	1
Argentina	1	1	1	Thailand	2	1	1
Brazil	1	1	1	India	1	1	1
Chile	1	1	2	Saudi Arabia	2	1	1
Mexico	1	1	2	South Africa	2	1	1
Peru	1	1	1	Turkey	2	1	2
Australia	1	1	2	Norway	1	1	2
Canada	2	1	1	Sweden	1	1	1
New Zealand	1	1	2	Switzerland	2	1	2
Indonesia	1	1	1	United Kingdom	2	1	1
Korea	2	1	1	United States	2	1	2

from 3 to 2; Peru from 3 to 1; the Philippines from 2 to 1; Saudi Arabia from 2 to 1; Singapore from 3 to 1; South Africa from 2 to 1; Thailand from 2 to 1; and the United Kingdom from 3 to 1. This shrinkage in the number of cointegration relations proved necessary for arriving at convergent persistent profiles for the various cointegration relations. The persistence profiles refer to the time profiles of the effects of system- or variable-specific shocks on the cointegration relations in the GVAR model.[22] The value of these profiles is unity on impact, while it should tend to zero as n (the horizon of the persistence profiles) tends to infinity, if the vector under investigation is indeed a cointegration vector. The persistence profiles of the system suggest that all cointegrating relationships return to their long-run equilibrium within a ten-year period after a shock to the system; see figure C1 for persistence profiles of the model solved using the 2009 trade matrix for a selection of cointegrating vectors.

Weak Exogeneity Tests

To test for weak exogeneity, we employ the procedure proposed by Johansen and by Harbo and others.[23] This is a test on the joint significance of the estimated error correction terms in auxiliary equations for the country-specific

22. See Pesaran and Shin (1996).
23. Johansen (1992); Harbo and others (1998).

TABLE C4. Lag Trace Statistics for Testing for Cointegration in Country-Specific Models

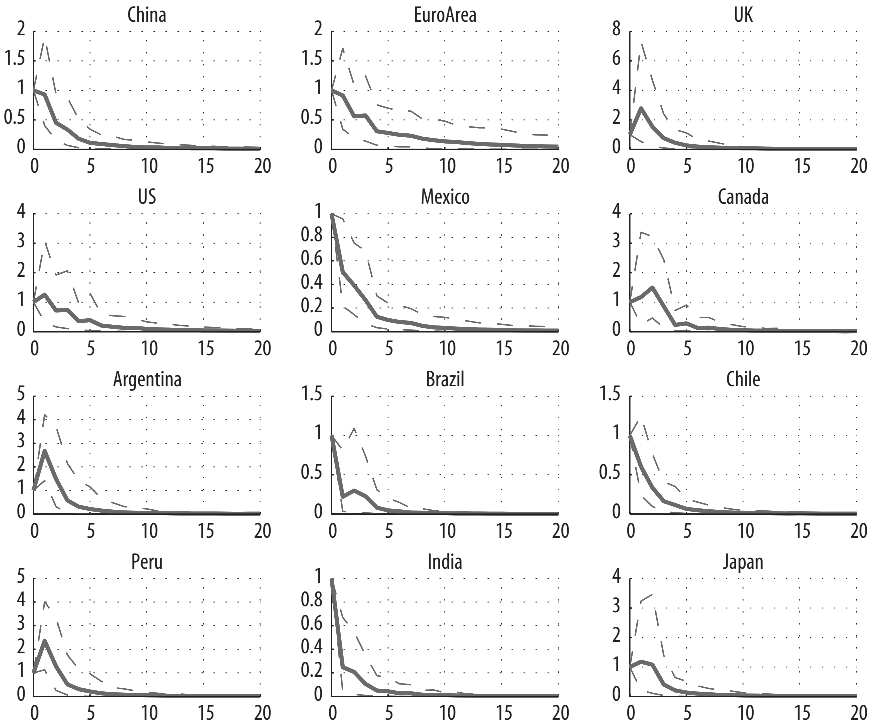
Statistic	*Argentina*	*Australia*	*Brazil*	*Canada*	*Chile*	*China*	*Euro area*	*India*	*Indonesia*	*Japan*	*Korea*	*Malaysia*	*Mexico*
# End.	5	6	4	6	5	4	6	5	4	6	6	5	4
# For.	6	6	6	6	6	6	6	6	6	6	6	6	6
r=0	463.92	346.99	323.50	267.86	309.50	164.88	260.99	198.45	184.13	281.53	331.90	184.51	220.10
r=1	177.79	238.33	79.77	185.18	195.00	93.17	184.31	128.08	108.25	179.38	251.37	117.86	112.25
r=2	85.46	160.67	27.76	121.47	113.19	42.53	117.86	78.35	55.14	122.16	172.91	65.44	58.50
r=3	27.10	92.40	9.60	79.31	58.36	19.46	76.11	43.58	21.09	72.12	98.15	29.89	22.82
r=4	12.17	48.73	—	47.45	18.79	—	42.97	14.06	—	46.16	49.84	11.65	—
r=5	—	17.66	—	18.49	—	—	14.93	—	—	21.45	21.30	—	—

Statistic	*Norway*	*N.Zealand*	*Peru*	*Philippines*	*S.Arabia*	*S.Africa*	*Singapore*	*Sweden*	*Switzerland*	*Thailand*	*Turkey*	*U.K.*	*U.S.*
# End.	6	6	4	5	3	6	5	6	6	5	4	6	6
# For.	6	6	6	6	6	6	6	6	6	6	6	6	4
r=0	324.61	372.98	324.37	235.27	132.99	256.73	221.21	242.69	263.17	201.07	148.50	299.36	273.46
r=1	193.59	258.27	136.16	144.09	70.50	172.69	137.33	153.24	178.68	129.14	92.88	175.62	185.14
r=2	116.41	162.13	66.59	68.04	23.82	114.65	89.46	99.14	115.50	73.32	46.23	120.40	105.22
r=3	72.90	80.70	16.03	30.48	—	62.03	52.21	60.61	70.20	43.06	15.67	77.74	66.76
r=4	30.75	44.49	—	7.42	—	35.16	17.91	33.79	37.04	18.39	—	37.70	29.77
r=5	9.58	21.82	—	—	—	15.23	—	12.74	13.01	—	—	15.61	11.81

TABLE C5. Critical Values for Trace Statistics at the Five Percent Significance Level

Statistic	*Argentina*	*Australia*	*Brazil*	*Canada*	*Chile*	*China*	*Euro area*	*India*	*Indonesia*	*Japan*	*Korea*	*Malaysia*	*Mexico*
# End.	5	6	4	6	4	5	6	5	4	6	6	5	4
# For.	6	6	6	6	6	6	6	6	6	6	6	6	6
r=0	156.44	197.70	119.03	197.70	119.03	156.44	197.70	156.44	119.03	197.70	197.70	156.44	119.03
r=1	119.03	156.44	85.44	156.44	85.44	119.03	156.44	119.03	85.44	156.44	156.44	119.03	85.44
r=2	85.44	119.03	55.50	119.03	55.50	85.44	119.03	85.44	55.50	119.03	119.03	85.44	55.50
r=3	55.50	85.44	28.81	85.44	28.81	55.50	85.44	55.50	28.81	85.44	85.44	55.50	28.81
r=4	28.81	55.50	—	55.50	—	28.81	55.50	28.81	—	55.50	55.50	28.81	—
r=5	—	28.81	—	28.81	—	—	28.81	—	—	28.81	28.81	—	—
Statistic	*Norway*	*N.Zealand*	*Peru*	*Philippines*	*S.Arabia*	*S.Africa*	*Singapore*	*Sweden*	*Switzerland*	*Thailand*	*Turkey*	*U.K.*	*U.S.*
# End.	6	6	4	5	6	3	5	6	6	5	4	6	6
# For.	6	6	6	6	6	6	6	6	6	6	6	6	4
r=0	197.70	197.70	119.03	156.44	197.70	85.44	156.44	197.70	197.70	156.44	119.03	197.70	171.33
r=1	156.44	156.44	85.44	119.03	156.44	55.50	119.03	156.44	156.44	119.03	85.44	156.44	134.16
r=2	119.03	119.03	55.50	85.44	119.03	28.81	85.44	119.03	119.03	85.44	55.50	119.03	100.96
r=3	85.44	85.44	28.81	55.50	85.44	—	55.50	85.44	85.44	55.50	28.81	85.44	71.56
r=4	55.50	55.50	—	28.81	55.50	—	28.81	55.50	55.50	28.81	—	55.50	45.90
r=5	28.81	28.81	—	—	28.81	—	—	28.81	28.81	—	—	28.81	23.63

FIGURE C1. Persistence Profiles for a Selection of Cointegrating Vectors: Bootstrapped PPs, 2009



foreign variables, $\mathbf{x}^*_{it}$. In particular, we estimated the following regression for each *lth* element of $\mathbf{x}^*_{it}$:

$$\text{(C1)}\quad \Delta \mathbf{x}^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} ECM^j_{i,t-1} + \sum_{k=1}^{s_i} \varphi_{ik,l} \Delta \mathbf{x}_{i,t-k} + \sum_{m=1}^{n_i} \vartheta_{im,l} \Delta \tilde{\mathbf{x}}^*_{i,t-m} + \varepsilon_{it,l},$$

where $ECM^j_{i,t-1}$, $j = 1, 2, \ldots r_i$ are the estimated error correction terms corresponding to the r_i cointegrating relations found for the *ith* country model, and $\Delta \mathbf{x}^*_{it} = [\Delta \mathbf{x}^*_{it}, \Delta(e^*_{it} - p^*_{it}), \Delta p^o_t]'$.[24] The weak exogeneity test is an F test of joint hypothesis that $\gamma_{ij,l} = 0$ for each $j = 1, 2, \ldots r_i$. In this case, we take the lag orders *si* to be the same as the orders p_i of the underlying country-specific VARX* models, and we set the lag order n_i to two for all countries, following Dees and others (see table C6).[25]

24. In the case of the United States, the variable $\Delta(e^*it - p^*it)$ is implicitly included in $\Delta \mathbf{x}^*it$.
25. Dees and others (2007).

TABLE C6. *F* Statistics for Testing the Weak Exogeneity of the Country-Specific Foreign Variables and Oil Prices

Country	*F test*	*Critical value*	y^*	π^*	q^*	$e^* - p^*$	ρ^{S*}	ρ^{L*}	p^0
Argentina	F(1,99)	3.94	3.79	0.00	2.25		0.35	0.36	0.07
Australia	F(2,97)	3.09	0.27	0.13	0.67		0.41	0.56	0.36
Brazil	F(1,100)	3.94	0.07	0.78	0.04		0.11	0.11	4.74*
Canada	F(1,92)	3.94	0.12	0.50	0.26		2.08	0.18	0.03
Chile	F(2,98)	3.09	0.79	1.07	0.17		1.34	0.80	0.41
China	F(1,100)	3.94	0.06	0.02	0.03		0.90	3.81	1.65
Euro area	F(1,92)	3.94	0.48	1.26	0.24		0.02	2.72	2.31
India	F(1,99)	3.94	0.09	0.06	0.51		0.32	0.03	2.85
Indonesia	F(1,100)	3.94	0.16	0.20	1.87		0.07	0.80	0.11
Japan	F(1,92)	3.94	0.04	1.24	0.25		4.44*	5.67*	3.18
Korea	F(1,92)	3.94	0.02	1.07	2.38		0.03	0.13	1.19
Malaysia	F(1,99)	3.94	2.94	3.66	5.28*		1.74	0.02	3.41
Mexico	F(2,99)	3.09	3.44*	0.31	1.03		1.27	1.59	0.05
Norway	F(2,97)	3.09	0.83	3.73*	0.16		1.83	0.76	3.81*
New Zealand	F(2,97)	3.09	2.29	1.54	0.16		0.09	0.15	1.08
Peru	F(1,100)	3.94	1.40	2.15	0.49		1.14	0.09	1.63
Philippines	F(1,94)	3.94	4.16*	1.80	1.43		0.00	0.25	4.01*
Saudi Arabia	F(1,98)	3.94	0.09	0.66	0.84		0.20	0.04	0.03
South Africa	F(1,92)	3.94	1.15	0.60	0.65		0.42	2.66	0.14
Singapore	F(1,99)	3.94	0.53	0.09	0.72		0.05	2.53	0.00
Sweden	F(1,98)	3.94	0.24	0.36	0.58		0.99	0.04	0.06
Switzerland	F(2,91)	3.10	2.08	0.58	2.03		0.12	0.51	0.07
Thailand	F(1,94)	3.94	0.01	0.72	0.01		0.01	0.04	0.45
Turkey	F(2,95)	3.09	0.68	1.70	0.02		2.92	0.15	0.45
United Kingdom	F(1,98)	3.94	0.53	3.58	1.03		1.29	0.24	2.50
United States	F(2,93)	3.09	0.65	0.06	3.12*	0.45	2.12	0.42	

*Statistically significant at the 5 percent level.

Parameter Stability Tests

To test for parameter stability, we perform a battery of tests following Dees and others, based on the residuals of the individual equations of the country-specific error correction models.[26] In particular, we consider Ploberger and Kramer's maximal OLS cumulative sum (CUSUM) statistic, denoted by PK_{sup},

26. Dees and others (2007). These residuals only depend on the rank of the cointegrating vectors and do not depend on the way the cointegrating relations are exactly identified. We thus render the structural stability tests of the short-run coefficients invariant to exact identification of the long-run relations.

TABLE C7. Number of Rejections of the Null Hypothesis of Parameter Constancy per Variable across the Country-Specific Models[a]

Country	y	π	q	$e-p$	r^S	r^L	*Total*
PK_{sup}	10	5	4	2	4	1	26
PK_{msq}	9	3	1	2	2	1	18
ℵ	5	3	5	10	3	4	30
Robust ℵ	4	2	1	7	1	2	17
QLR	6	10	9	13	12	5	55
Robust *QLR*	2	5	4	8	1	4	24
MW	5	5	5	10	2	5	32
Robust *MW*	5	5	5	10	2	4	31
APW	6	9	9	12	12	6	54
Robust *APW*	3	5	4	9	2	5	28

a. The test statistics PK_{sup} and PK_{msq} are based on the cumulative sums of OLS residuals, ℵ is the Nyblom test for time-varying parameters, and QLR, MW, and APW are the sequential Wald statistics for a single break at an unknown change point. Statistics with the prefix robust denote the heteroskedasticity-robust version of the tests. All tests are implemented at the 5 percent significance level.

and its mean square variant, PK_{msq}.[27] Also included are tests for parameter constancy against nonstationary alternatives proposed by Nyblom, denoted by ℵ, as well as sequential Wald type tests of a one-time structural change at an unknown change point.[28] The latter include the Wald form of the Quandt likelihood ratio (QLR) statistic, Hansen's mean Wald statistic (MW) and Andrews and Ploberger's Wald (APW) statistic based on the exponential average.[29] The heteroskedasticity-robust versions of the above tests are also reported.

The tests show that most regression coefficients are stable once the individual equations are conditioned on the contemporaneous foreign variables. Tables C7 and C8 summarize the results of these tests by variable at the 5 percent significance level. The critical values of the tests, computed under the null hypothesis of parameter stability, are computed using the bootstrap samples obtained from the solution of the GVAR model. Similar to Dees and others, we note that the outcomes for the ℵ, QLR, and APW tests very much depend on whether heteroskedasticity-robust versions of these tests are used.[30] The

27. Ploberger and Kramer (1992). The $PK_{\sup}$ statistic is similar to the CUSUM test suggested by Brown, Durbin, and Evans (1975), although the latter is based on recursive rather than OLS residuals. The Ploberger and Kramer (1992) maximal OLS cumulative sum (CUSUM) statistic rejects the null hypothesis of parameter constancy whenever the maximum cumulated sum of OLS residuals becomes too large in absolute value.

28. Nyblom (1989).

29. Quandt (1960); Hansen (2002); Andrews and Ploberger (1994).

30. Dees and others (2007).

TABLE C8. Break Dates Computed with Quandt's Likelihood Ratio Statistic[a]

Country	y	π	q	$e-p$	ρ^S	ρ^L	p^0
Argentina	1989Q3	1989Q3	1989Q4	1989Q2	1989Q3	—	—
Australia	1989Q1	1987Q3	1987Q4	2000Q1	1987Q1	1989Q1	—
Brazil	1990Q1	1989Q3	—	1999Q1	1989Q3	—	—
Canada	1987Q1	2001Q3	2000Q4	2001Q3	1987Q1	1997Q3	—
Chile	1987Q1	1987Q1	1987Q3	2000Q4	1987Q4	—	—
China	2002Q2	1988Q3	—	1991Q1	1990Q1	—	—
Euro area	1987Q4	1990Q1	1992Q3	1998Q4	1988Q3	1989Q2	—
India	1996Q2	1997Q3	1992Q2	2002Q1	1994Q4	—	—
Indonesia	1998Q1	1997Q4	—	1997Q2	1995Q1	—	—
Japan	1991Q1	1987Q1	1993Q1	1995Q2	1987Q3	1995Q4	—
Korea	1998Q2	1987Q3	1997Q2	1998Q1	1998Q3	1987Q1	—
Malaysia	1997Q3	2002Q2	1998Q3	1997Q2	1998Q2	—	—
Mexico	1988Q3	1988Q1	—	1995Q1	1988Q1	—	—
Norway	2001Q2	2000Q4	1990Q1	2002Q1	1998Q4	1990Q4	—
New Zealand	1987Q2	1987Q1	1991Q2	2000Q3	1987Q2	1987Q2	—
Peru	1990Q1	1989Q4	—	1989Q4	1989Q4	—	—
Philippines	1987Q4	1987Q1	1987Q1	1987Q3	1987Q1	—	—
Saudi Arabia	1990Q2	1997Q3	—	1995Q2	—	—	—
South Africa	1987Q1	1994Q2	1988Q1	1989Q1	1997Q4	1989Q3	—
Singapore	1997Q3	1989Q4	1991Q3	1997Q3	1995Q3	—	—
Sweden	1987Q1	1993Q2	1988Q1	2000Q1	1991Q1	1988Q1	—
Switzerland	1987Q1	1987Q3	1987Q4	1992Q4	1989Q2	2001Q3	—
Thailand	1993Q2	1992Q4	1990Q3	1997Q4	1994Q4	—	—
Turkey	1993Q4	1994Q2	—	2000Q4	1994Q2	—	—
United Kingdom	1987Q1	1990Q4	1987Q1	1988Q4	1987Q4	1987Q1	—
United States	1987Q1	2000Q4	2000Q3	—	1987Q1	1988Q2	1998Q4

a. All tests are implemented at the 5 percent significance level.

nonrobust versions of the $\aleph$, QLR, and APW tests show a relatively large number of rejections, with the latter two tests leading to rejection of the joint null hypothesis of coefficient and error variance stability. Once possible changes in error variances are allowed, the parameter coefficients seem to have been reasonably more stable. The robust versions of the tests performed indicate that the remaining instability is mainly confined to error variances, without affecting most of the estimated coefficients. We address the problem of unstable error variances by using robust standard errors when investigating the impact effects of the foreign variables and impulse responses. Nonetheless, some parameter instability remains even after accounting for heteroskedasticity in the error variances. Table C8 presents the break dates with the QLR statistics at the 5 percent significance level.

Contemporaneous Effects of Foreign Variables on Their Domestic Counterparts

The estimation of the cointegrating VARX* models permits us to examine the impact of foreign variables on their domestic counterparts, by looking at the estimated coefficients corresponding to the contemporaneous foreign variables in the country-specific models. These estimates can be viewed as impact elasticities, which measure the contemporaneous variation of a domestic variable due to a 1 percent change in its corresponding foreign-specific counterpart. In the GVAR framework, they are informative on the short-term comovements implied by the estimated model across different countries.

Table C9 presents these impact elasticities with the corresponding standard deviations (in parentheses), computed based on White's heteroskedasticity-consistent variance estimator. As in earlier work by Pesaran, Schuermann, and Weiner and by Dees and others, there is substantial comovement between the major advanced economies' output and their foreign counterparts.[31] The same result holds—with larger magnitudes—for most of the East Asian countries in the sample. Inflation transmission in these economies is less pronounced, but still positive and statistically significant. Contemporaneous elasticities for real equity prices are remarkably close to unity in the case of the euro area and Canada, reflecting their high degree of financial integration.

For the Latin American economies in our sample, these impact multipliers have the expected signs in most cases: foreign output elasticities for Argentina, Brazil, Chile, and Mexico are positive and statistically significant. Notably, Argentina exhibits the largest output impact elasticity. The results for inflation are very different, with all countries having coefficients close to zero and with none of the foreign inflation impact effects being statistically significant.

For the two Latin American countries with data on equity prices, we do observe a statistically significant contemporaneous response to changes in their foreign counterparts. Argentina shows an overreaction coefficient of 1.26, while Chile reacts only partially, with a lower coefficient of 0.51. This may reflect the relative differences in capital account openness between these two countries during the sample period. Short-term interest rates in Argentina exhibit an unusually high responsiveness to changes in their foreign counterparts. This is consistent with the low degree of monetary policy independence during the period of the currency board in Argentina (1991–2002), when the Argentine peso was pegged to the U.S. dollar. Different degrees of fixed

31. Pesaran, Schuermann, and Weiner (2004); Dees and others (2007).

TABLE C9. Contemporaneous Effects of Foreign Variables on Domestic Counterparts by Country[a]

Country	y	π	q	$e-p$	ρ^S	ρ^L
Argentina	0.83	–0.04	1.26	—	1.61	—
	(0.22)	(2.36)	(0.40)	—	(2.40)	—
Australia	0.34	0.77	0.81	—	0.45	0.89
	(0.12)	(0.18)	(0.14)	—	(0.11)	(0.15)
Brazil	0.59	3.30	—	—	0.46	—
	(0.23)	(2.52)	—	—	(4.10)	—
Canada	0.48	0.68	0.94	—	0.51	1.04
	(0.09)	(0.11)	(0.05)	—	(0.17)	(0.07)
Chile	0.77	0.11	0.51	—	0.13	—
	(0.24)	(0.07)	(0.12)	—	(0.07)	—
China	0.71	0.64	—	—	0.02	—
	(0.22)	(0.29)	—	—	(0.04)	—
Euro area	0.42	0.18	1.02	—	0.09	0.69
	(0.09)	(0.08)	(0.04)	—	(0.02)	(0.08)
India	0.06	0.68	0.78	—	–0.04	—
	(0.14)	(0.33)	(0.14)	—	(0.07)	—
Indonesia	0.99	0.86	—	—	0.98	—
	(0.41)	(0.69)	—	—	(0.83)	—
Japan	0.10	0.10	0.72	—	–0.05	0.50
	(0.16)	(0.09)	(0.10)	—	(0.05)	(0.08)
Korea	–0.08	0.70	0.94	—	–0.21	0.21
	(0.19)	(0.29)	(0.17)	—	(0.13)	(0.32)
Malaysia	1.26	0.61	1.11	—	0.00	—
	(0.34)	(0.17)	(0.20)	—	(0.09)	—
Mexico	0.63	0.77	—	—	0.01	—
	(0.17)	(0.56)	—	—	(0.54)	—
Norway	1.33	0.78	1.14	—	0.36	0.70
	(0.31)	(0.20)	(0.09)	—	(0.20)	(0.15)
New Zealand	0.33	0.42	0.82	—	0.51	0.39
	(0.19)	(0.18)	(0.11)	—	(0.28)	(0.22)
Peru	0.15	–0.58	—	—	–2.38	—
	(0.43)	(2.44)	—	—	(1.26)	—
Philippines	0.03	–0.24	1.02	—	0.30	—
	(0.22)	(0.52)	(0.20)	—	(0.32)	—
Saudi Arabia	0.42	0.11	—	—	—	—
	(0.37)	(0.20)	—	—	—	—
South Africa	0.16	0.15	0.90	—	0.01	0.44
	(0.14)	(0.24)	(0.14)	—	(0.07)	(0.22)
Singapore	0.86	0.32	1.27	—	0.27	—
	(0.25)	(0.17)	(0.12)	—	(0.14)	—
Sweden	1.36	1.31	1.23	—	0.40	0.94
	(0.28)	(0.16)	(0.09)	—	(0.17)	(0.16)
Switzerland	0.53	0.37	0.91	—	0.19	0.47
	(0.13)	(0.10)	(0.06)	—	(0.08)	(0.08)
Thailand	0.33	0.63	0.83	—	0.37	—
	(0.20)	(0.32)	(0.12)	—	(0.27)	—
Turkey	1.21	3.57	—	—	1.10	—
	(0.42)	(1.26)	—	—	(0.77)	—
United Kingdom	0.58	0.78	0.86	—	0.22	0.76
	(0.14)	(0.12)	(0.06)	—	(0.12)	(0.12)
United States	0.45	0.50	—	—	0.01	—
	(0.12)	(0.11)	—	—	(0.05)	—

a. White's heteroskedasticity-robust standard errors are in parentheses.

exchange rate regimes were also in place before and after the currency board period in Argentina.

Pairwise Cross-Section Correlations: Variables and Residuals

One of the basic assumptions underlying the GVAR model is that the cross-dependence of the variable-specific innovations must be sufficiently small, so that

$$\text{(C2)} \qquad \frac{\sum_{j=1}^{N} \sigma_{ij,ls}}{N} \to 0 \text{ } as \text{ } N \to \infty \text{ } \forall \text{ } i,ls,$$

where $\sigma_{ij,ls} = \text{cov}(u_{ilt}, u_{jst})$ is the covariance of the variable l in country i with the variable s in country j. Technically, this requires that the country-specific shocks are cross-sectionally weakly correlated. Following Dees and others, we check this condition by calculating the average pairwise cross-section correlations of all the variables in the GVAR, both in levels and in differences, as well as those of associated residuals from the country-specific VARX* models with foreign variables that we estimated in the first step of the GVAR analysis.[32] The number of cointegration relations and lag orders in the country-specific VARX* models are given in table C3. We also compute average pairwise cross-section correlations of the residuals from the VAR models, obtained after re-estimating all the individual country-specific models over the same period *excluding* the foreign variables, including oil as an endogenous variable in all the country models. For each country VAR model, we used the same lag order as specified in table C3 and selected the number of cointegration relationships based on Johansen's trace statistics computed for the individual VAR models excluding the foreign variables. The main rationale is that foreign variables could be considered as global factors for each of the countries considered in the GVAR model. Thus, the estimation of each country-specific model by conditioning on the foreign variables can take account of the common components, rendering the residuals cross-sectionally weakly correlated.

Tables C10 and C11 report the average pairwise cross sectional correlations for the domestic variables and the residuals of the VARX* models with foreign variables (column labeled ResX) and of the VAR models without foreign variables (column labeled Res). Although these results do not constitute a formal statistical test of the importance of the foreign variables

32. Dees and others (2007).

TABLE C10. Average Pairwise Cross-Section Correlations of Real GDP, Inflation, and Equity Price and the Associated Model's Residuals[a]

	Real GDP				Inflation				Equity price			
Country	*Levels*	*First diff.*	*Res*	*ResX*	*Levels*	*First diff.*	*Res*	*ResX*	*Levels*	*First diff.*	*Res*	*ResX*
Argentina	0.89	0.08	0.03	0.01	0.26	0.05	0.05	0.01	0.45	0.21	0.17	0.00
Australia	0.97	0.16	0.12	0.02	0.34	0.08	0.05	−0.02	0.79	0.52	0.47	0.05
Brazil	0.96	0.15	0.10	0.01	0.21	0.01	0.00	−0.05	—	—	—	—
Canada	0.97	0.20	0.10	0.02	0.41	0.14	0.11	0.02	0.73	0.54	0.48	0.05
Chile	0.96	0.16	0.09	0.02	0.39	0.05	−0.02	−0.01	0.78	0.29	0.28	0.06
China	0.97	0.09	0.06	−0.02	0.10	0.07	0.06	0.00	—	—	—	—
Euro area	0.96	0.26	0.16	0.01	0.46	0.16	0.13	0.03	0.78	0.56	0.52	−0.10
India	0.97	−0.02	−0.01	−0.01	0.19	0.03	0.06	0.01	0.77	0.32	0.29	0.00
Indonesia	0.96	0.10	0.06	−0.01	0.01	0.04	0.07	0.02	—	—	—	—
Japan	0.90	0.16	0.06	−0.03	0.42	0.09	0.05	−0.01	0.43	0.44	0.32	−0.11
Korea	0.95	0.13	0.06	0.02	0.37	0.06	0.05	0.00	0.70	0.36	0.30	−0.02
Malaysia	0.96	0.21	0.13	0.02	0.27	0.11	0.09	0.01	0.60	0.39	0.38	0.06
Mexico	0.96	0.17	0.12	0.02	0.19	0.01	0.02	0.00	—	—	—	—
Norway	0.97	0.12	0.11	0.03	0.37	0.08	0.06	0.03	0.81	0.49	0.46	0.06
New Zealand	0.96	0.18	0.10	0.06	0.33	0.07	0.04	0.03	0.54	0.40	0.37	0.02
Peru	0.85	0.06	0.06	0.01	0.23	−0.04	0.00	−0.03	—	—	—	—
Philippines	0.94	0.07	0.03	0.01	0.21	0.03	0.03	0.00	0.72	0.36	0.34	0.03
Saudi Arabia	0.89	0.03	0.05	−0.02	0.05	0.00	0.06	0.03	—	—	—	—
South Africa	0.94	0.20	0.11	0.05	0.33	0.06	0.04	0.04	0.79	0.47	0.41	0.07
Singapore	0.96	0.20	0.14	0.00	0.30	0.06	0.07	0.01	0.73	0.53	0.49	0.01
Sweden	0.96	0.21	0.16	0.01	0.46	0.10	0.11	0.01	0.77	0.50	0.47	−0.02
Switzerland	0.96	0.20	0.11	0.00	0.39	0.09	0.07	0.02	0.79	0.53	0.51	0.01
Thailand	0.94	0.18	0.07	0.02	0.31	0.06	0.02	−0.01	0.64	0.39	0.36	0.06
Turkey	0.96	0.13	0.08	0.00	0.14	0.00	0.04	−0.01	—	—	—	—
United Kingdom	0.97	0.21	0.15	0.03	0.45	0.11	0.12	0.02	0.77	0.55	0.50	−0.05
United States	0.97	0.22	0.11	−0.02	0.42	0.19	0.16	0.01	0.78	0.54	0.48	−0.02

a. ResX (VARX* residuals) refers to residuals from the country-specific VARX* models with foreign variables, estimated in the first step of the GVAR analysis. The number of cointegration relations and lag orders in the country-specific VARX* models are given in table C3. Res (VAR residuals) is obtained after re-estimating all the individual country-specific models over the same period excluding the foreign variables, including oil as endogenous in all the country models. For each country VAR model, we used the same lag order as specified in table C3 and selected the number of cointegration relationships based on Johansen's trace statistics computed for the individual VAR models excluding the foreign variables.

TABLE C11. Average Pairwise Cross-Section Correlations of Exchange Rate, Short-Term Interest Rate, and Long-Term Interest Rate and the Associated Model's Residuals[a]

	Real exchange rate				*Short-term interest rate*				*Long-term interest rate*			
Country	*Levels*	*First diff.*	*Res*	*ResX*	*Levels*	*First diff.*	*Res*	*ResX*	*Levels*	*First diff.*	*Res*	*ResX*
Argentina	0.42	0.09	0.07	0.07	0.42	0.03	0.02	−0.02	—	—	—	—
Australia	0.76	0.36	0.30	0.24	0.55	0.13	0.08	0.00	0.85	0.37	0.28	0.02
Brazil	0.70	0.18	0.13	0.11	0.36	0.01	0.00	−0.07	—	—	—	—
Canada	0.72	0.31	0.21	0.18	0.60	0.18	0.15	0.10	0.87	0.37	0.32	−0.01
China	0.19	0.08	0.03	0.02	0.49	0.07	0.05	0.02	—	—	—	—
Chile	0.64	0.27	0.21	0.16	0.57	0.02	−0.05	−0.04	—	—	—	—
Euro area	0.75	0.36	0.30	0.32	0.61	0.18	0.10	0.05	0.86	0.45	0.34	−0.05
India	0.33	0.24	0.21	0.17	0.34	0.10	0.05	0.04	—	—	—	—
Indonesia	0.05	0.22	0.14	0.12	0.15	0.08	0.07	0.04	—	—	—	—
Japan	0.64	0.17	0.14	0.16	0.57	0.05	0.02	0.00	0.83	0.28	0.23	−0.04
Korea	0.73	0.28	0.22	0.17	0.54	0.06	0.05	0.05	0.75	0.06	0.02	−0.05
Malaysia	0.62	0.29	0.23	0.21	0.43	0.06	0.02	0.05	—	—	—	—
Mexico	0.65	0.08	0.04	0.00	0.43	0.03	0.02	0.04	—	—	—	—
Norway	0.75	0.38	0.34	0.33	0.55	0.05	−0.02	−0.01	0.83	0.27	0.22	−0.01
New Zealand	0.75	0.36	0.30	0.27	0.49	0.06	0.05	0.01	0.76	0.19	0.12	0.02
Peru	0.70	0.05	0.06	0.05	0.40	0.04	0.04	0.05	—	—	—	—
Philippines	0.73	0.18	0.18	0.16	0.56	0.09	0.05	0.03	—	—	—	—
Saudi Arabia	0.44	0.07	0.05	0.07	—	—	—	—	—	—	—	—
South Africa	0.64	0.30	0.25	0.24	0.39	0.11	0.06	0.04	0.53	0.19	0.13	0.00
Singapore	0.74	0.37	0.30	0.26	0.51	0.09	0.08	0.02	—	—	—	—
Sweden	0.70	0.35	0.29	0.28	0.64	0.10	0.07	0.02	0.87	0.37	0.28	0.02
Switzerland	0.74	0.30	0.25	0.30	0.45	0.09	0.02	−0.02	0.74	0.37	0.21	0.01
Thailand	0.73	0.29	0.25	0.22	0.56	0.12	0.08	0.04	—	—	—	—
Turkey	0.73	0.19	0.13	0.07	0.15	0.05	0.04	0.01	—	—	—	—
United Kingdom	0.73	0.34	0.28	0.26	0.61	0.15	0.09	0.04	0.86	0.39	0.28	−0.04
United States	—	—	—	—	0.52	0.11	0.08	0.03	0.83	0.40	0.30	−0.02

a. ResX (VARX* residuals) refers to residuals from the country-specific VARX* models with foreign variables, estimated in the first step of the GVAR analysis. The number of cointegration relations and lag orders in the country-specific VARX* models are given in table C3. Res (VAR residuals) is obtained after re-estimating all the individual country-specific models over the same period excluding the foreign variables, including oil as endogenous in all the country models. For each country VAR model, we used the same lag order as specified in table C3 and selected the number of cointegration relationships based on the Johansen's trace statistics computed for the individual VAR models excluding the foreign variables.

in the GVAR model, they do provide an important indication of their usefulness in modeling global interdependencies, as the remaining correlation in the residuals is much lower than the one among the variables themselves. As illustrated by the differences between the two columns ResX and Res, the results also show that once country-specific models are formulated conditional on foreign variables, the degree of correlations across the shocks from different countries is sharply reduced.

Bootstrapped GIRFs

Figures C2 through C9 present bootstrapped generalized impulse response functions (GIRFs) for a one-standard-deviation increase in GDP in China, the United States, Latin America, and the rest of Asia, for 1985 and 2009.

FIGURE C2. GIRFs for One-Standard-Deviation Increase in Chinese GDP: Bootstrapped GIRFs, 2009

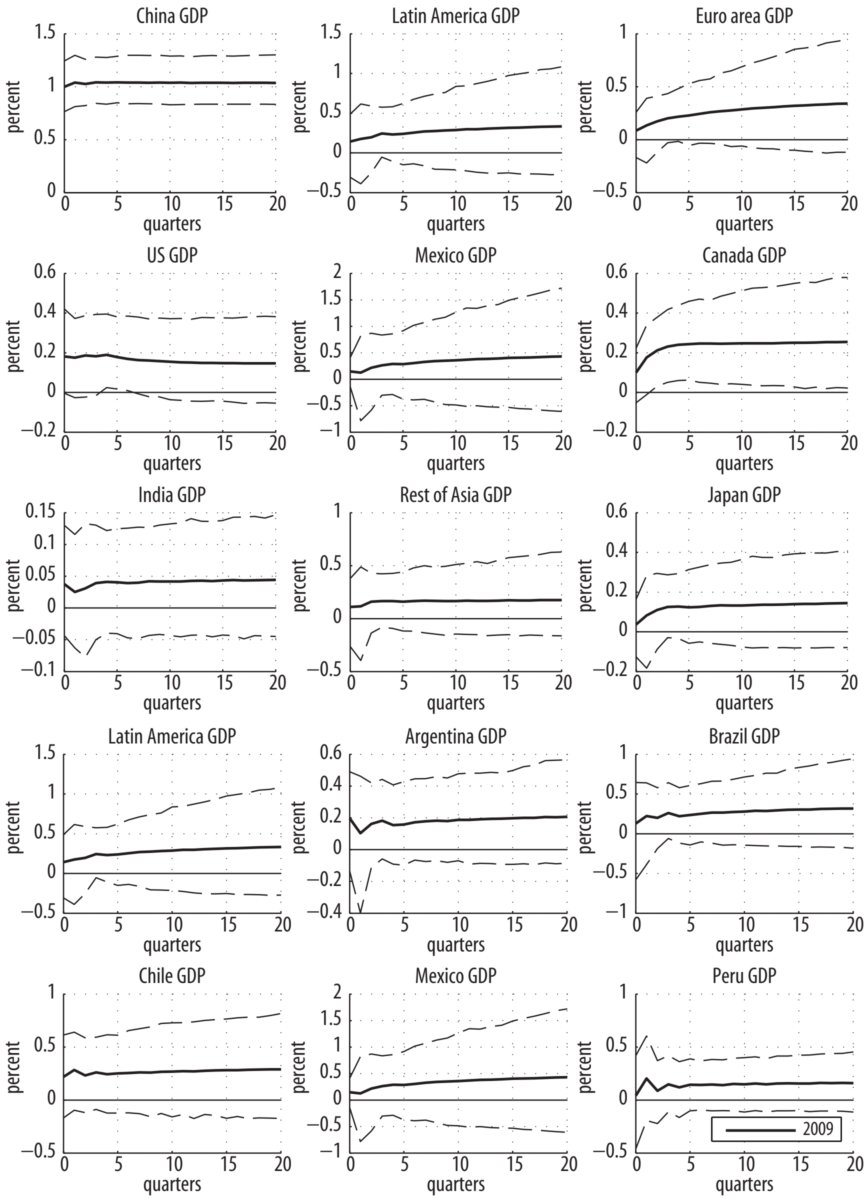


FIGURE C3. GIRFs for One-Standard-Deviation Increase in Chinese GDP: Bootstrapped GIRFs, 1985

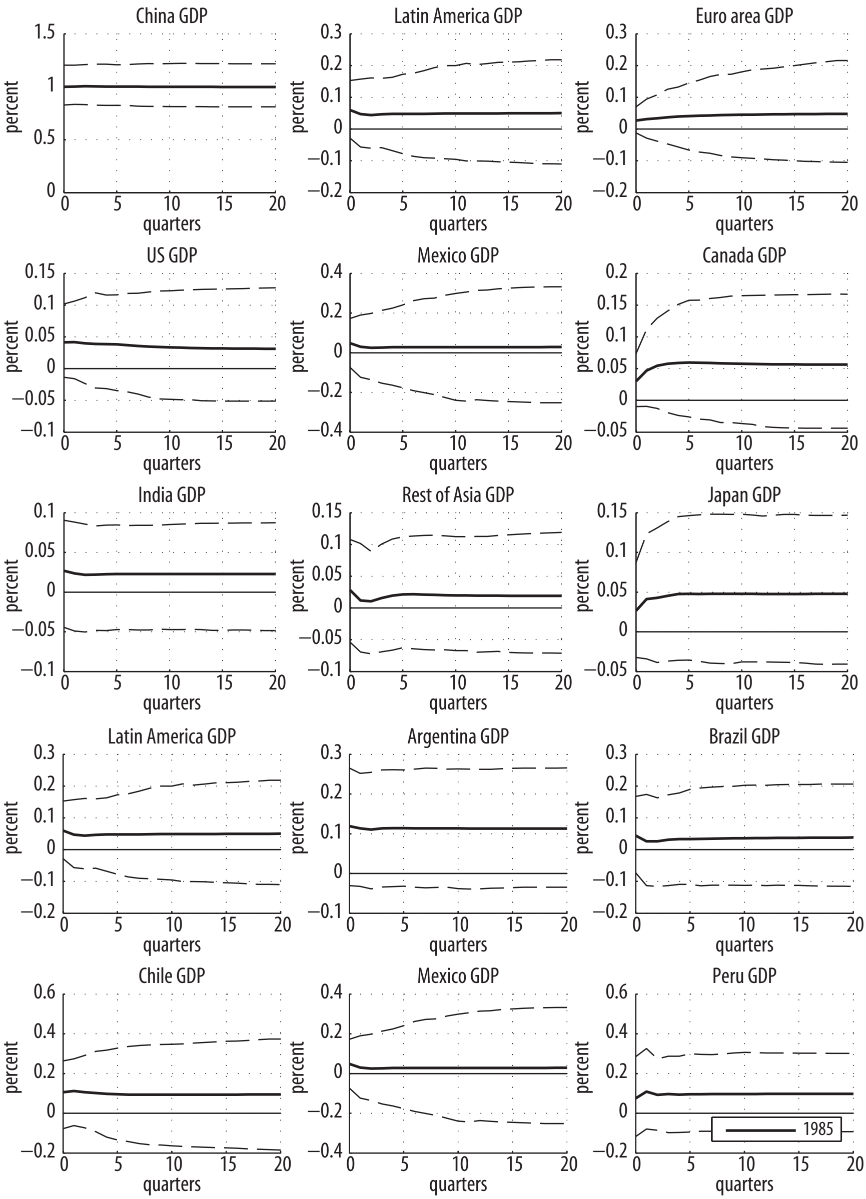


FIGURE C4. GIRFs for One-Standard-Deviation Increase in U.S. GDP: Bootstrapped GIRFs, 2009

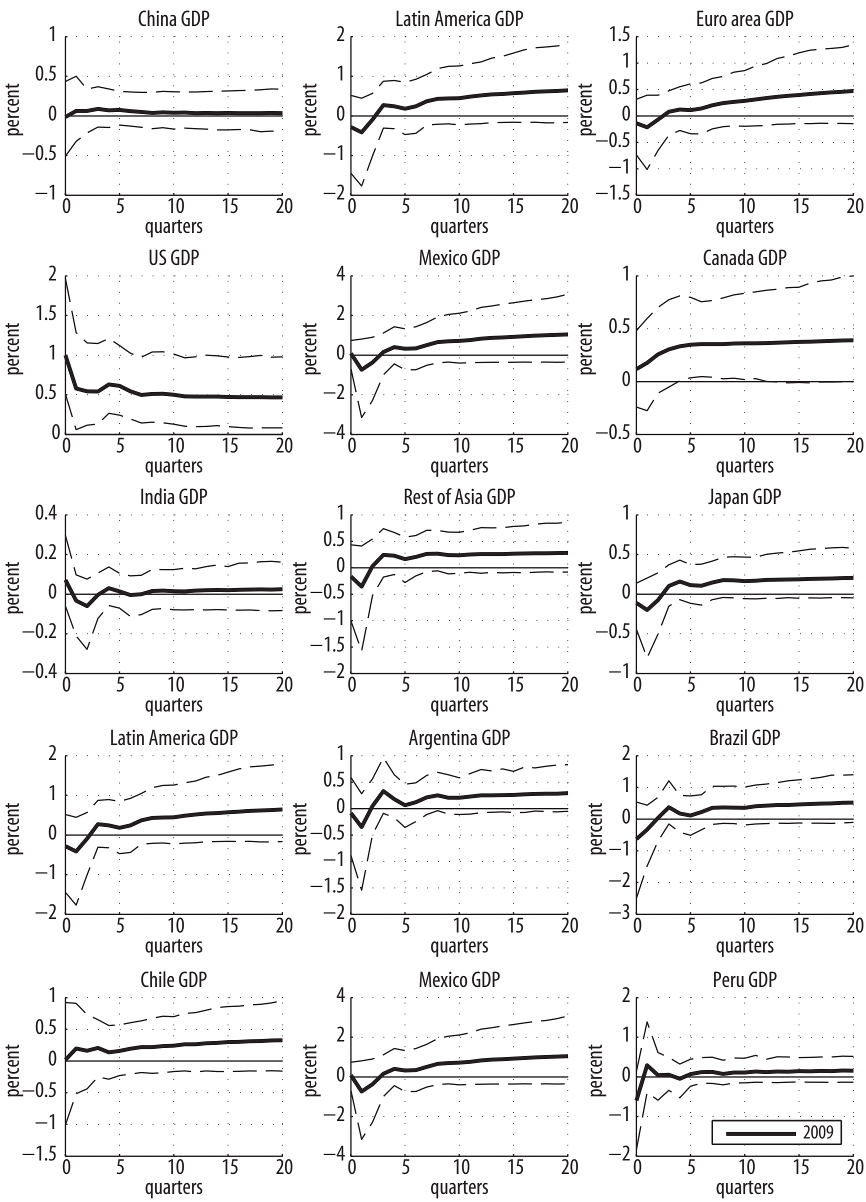


FIGURE C5. GIRFs for One-Standard-Deviation Increase in U.S. GDP: Bootstrapped GIRFs, 1985

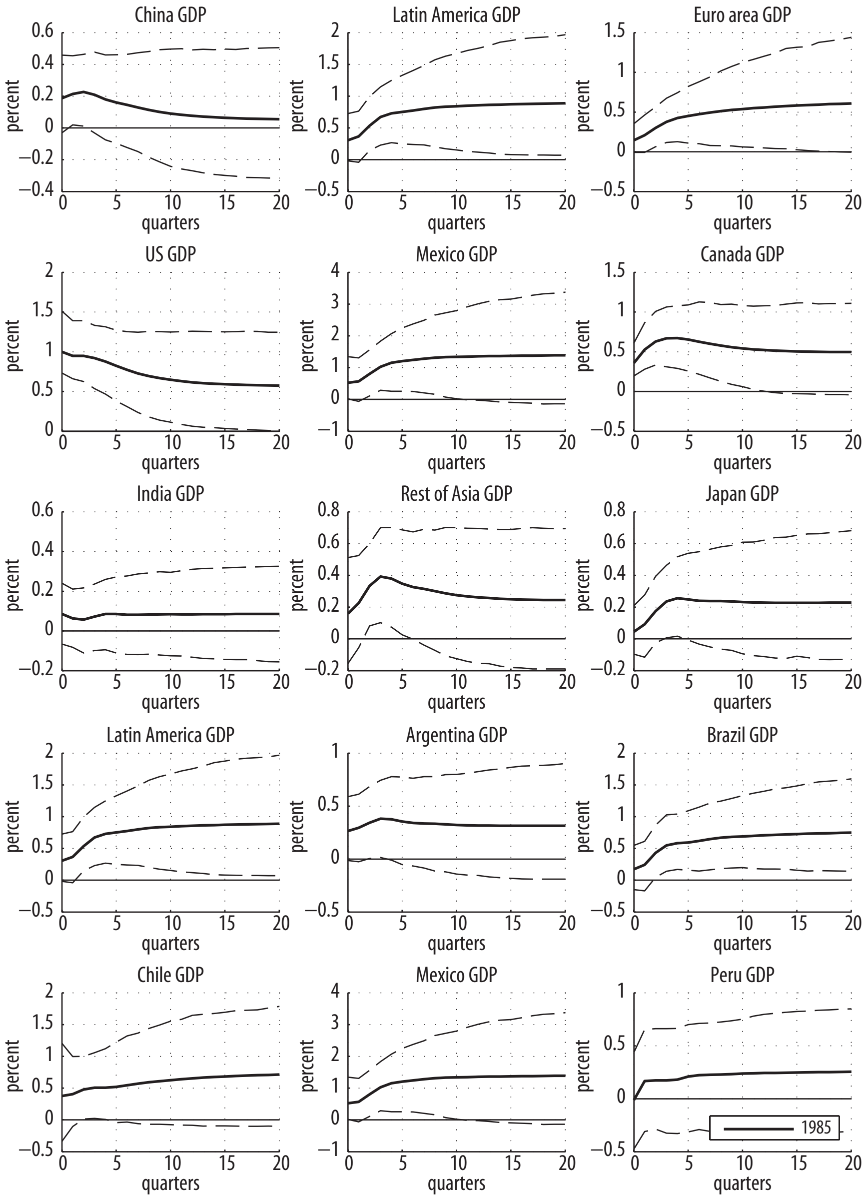


FIGURE C6. GIRFs for One-Standard-Deviation Increase in Latin American GDP: Bootstrapped GIRFs, 2009

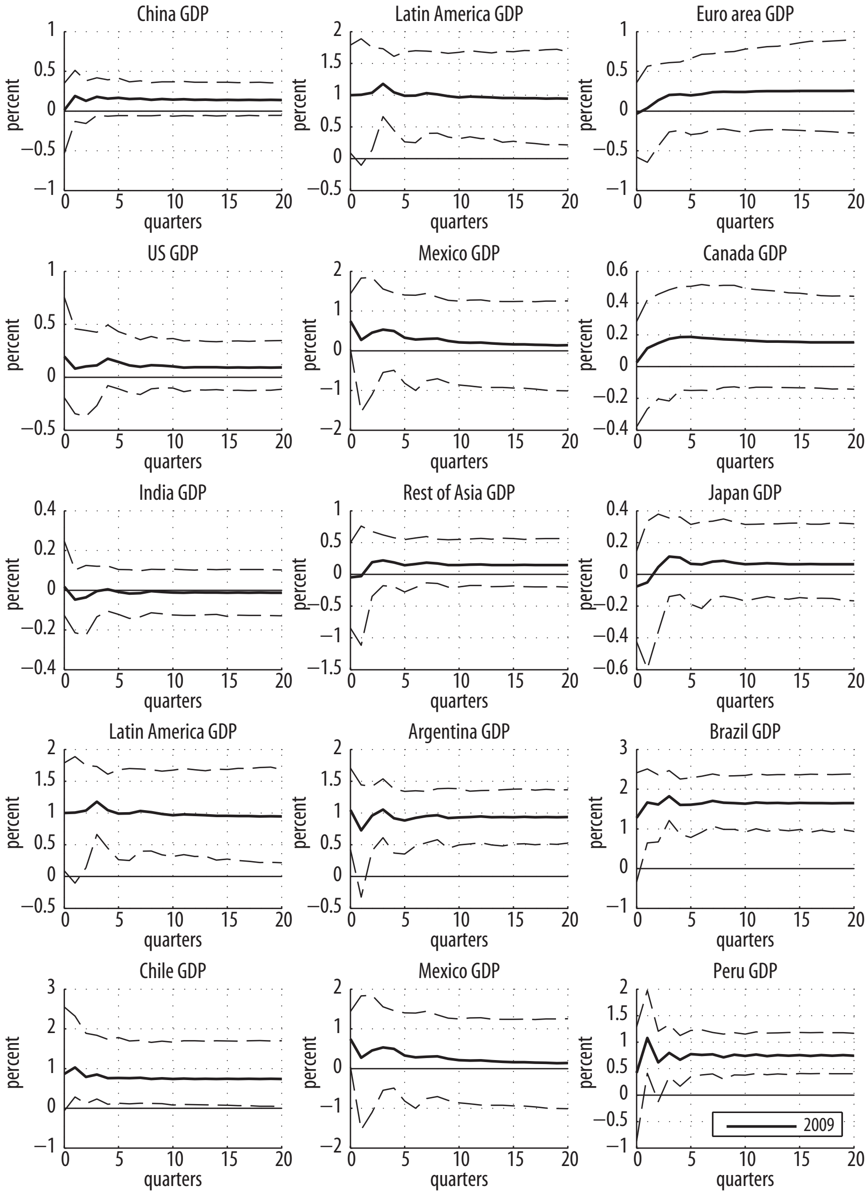


FIGURE C7. GIRFs for One-Standard-Deviation Increase in Latin American GDP: Bootstrapped GIRFs, 1985

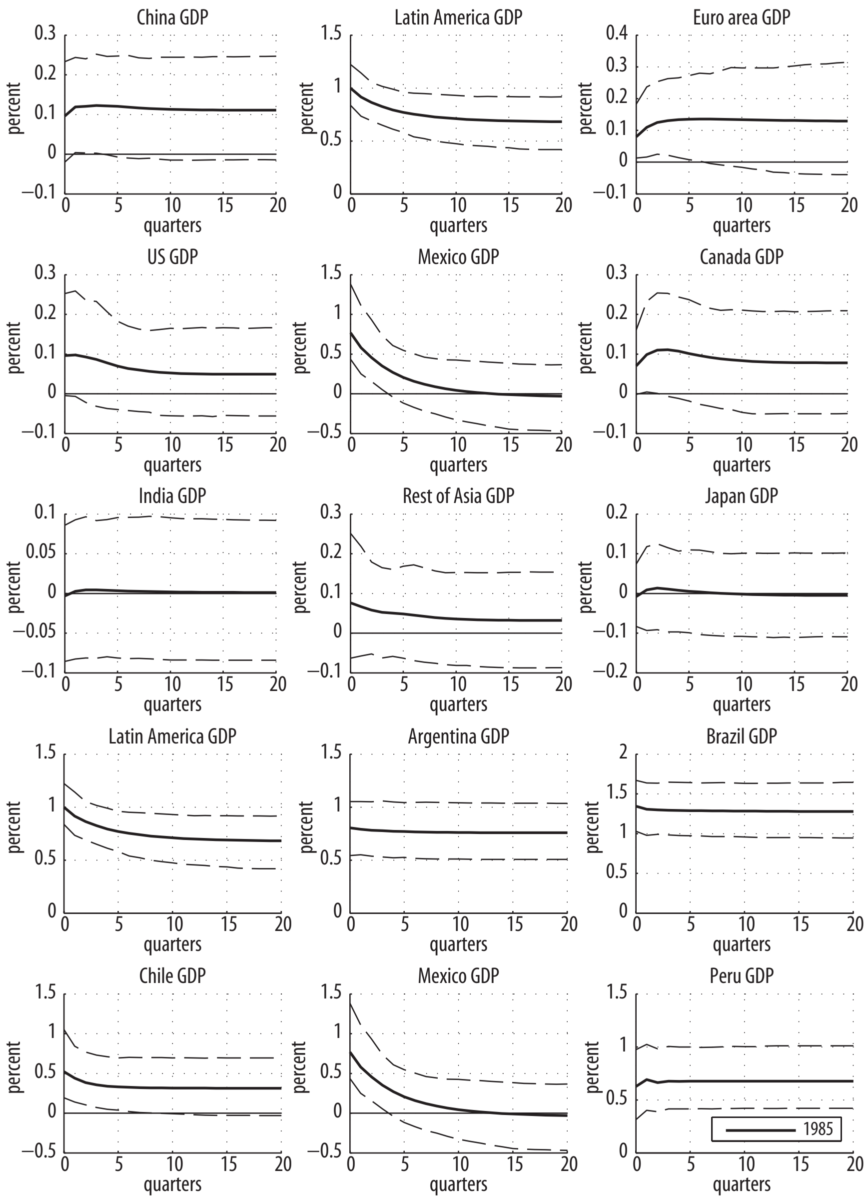


FIGURE C8. GIRFs for One-Standard-Deviation Increase in Rest of Asia's GDP: Bootstrapped GIRFs, 2009

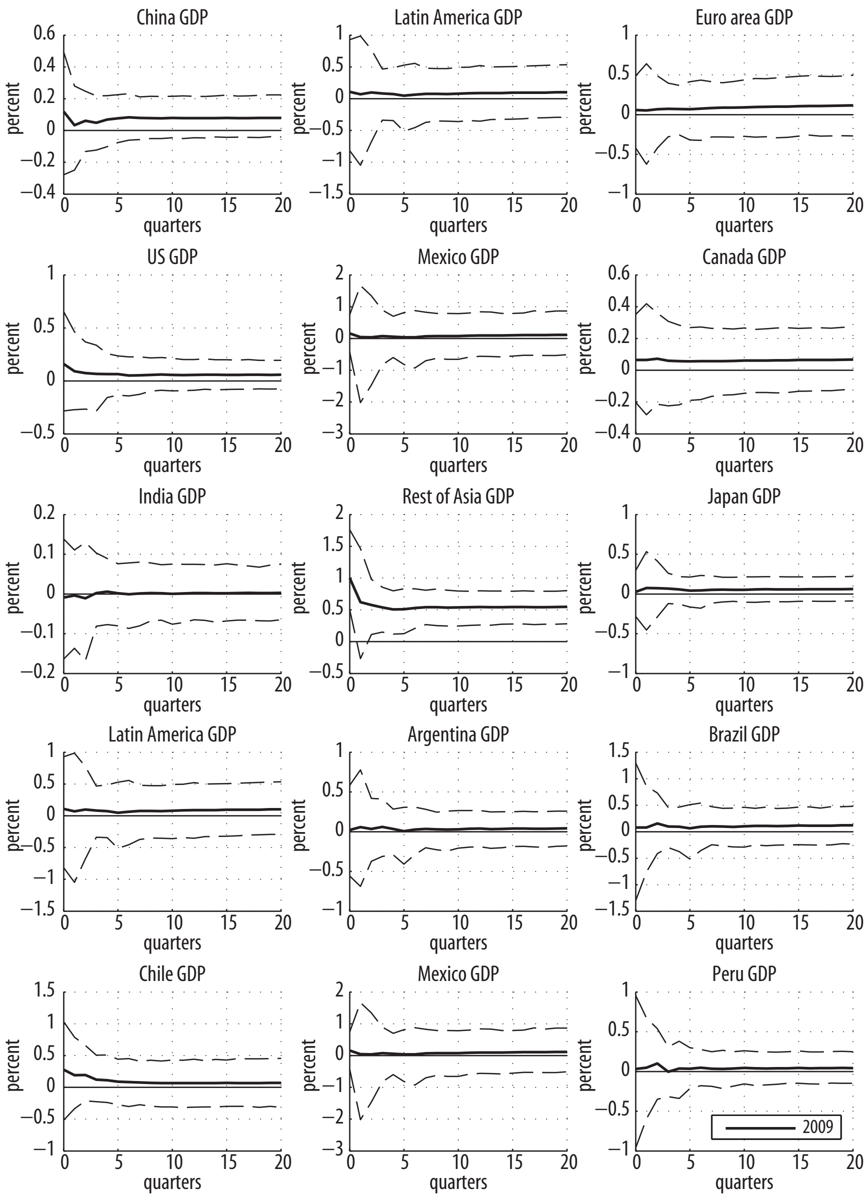


FIGURE C9. GIRFs for One-Standard-Deviation Increase in the Rest of Asia's GDP: Bootstrapped GIRFs, 1985