**BANCO CENTRAL DE RESERVA DEL PERÚ**

# Trade linkages and growth in Latin America: A time-varying SVAR approach

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**Abstract**

This paper examines how shocks originated in large economies around the globe have transmitted to the growth rates of Latin American countries. For this purpose, a highly parsimonious structural VAR model – identified through bilateral trade linkages – is proposed, tested, estimated and simulated. Since trade weights evolve through time, the effect of shocks are time-varying. Thus, we are able to quantify how growth in the region has been affected by tighter trading linkages with fast-growing emerging economies, and how it has responded to a new world trade structure, featuring China as a major player. It is found that about half of the vigourous growth reported in Latin American countries by the end of the 2000s can be attributed to (direct and especially indirect) multiplier effects induced by the spectacular growth of the Chinese economy over the same period.

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# 1   Introduction

It has been widely discussed that during the last two decades a new global context has emerged as the result of a deeper integration between countries and regions and because of the high growth of emerging countries, whose contribution to the world growth has been increasing. As reported by Izquierdo and Talvi (2011), the main traits of this new global economic order, which became evident after the 2008 financial crisis, are the reallocation of world output and demand from industrial countries to emerging markets, and the redirection of world savings providing abundant and inexpensive international resources to emerging economies.

The reallocation of world output and demand came in tandem with dramatic changes in trade patterns. For Latin American countries, there has been a substantial shift in its trade towards emerging markets. At the beginning of the 1990s, the United States was Latin America's main trade partner, followed by European countries, while the only Asian country among the top trade partners was Japan. In contrast, by the end of the last decade, China has become the main trade partner for Brazil, Chile and Peru, and advanced the ranking in the remaining Latin American countries. Also, whereas the United States remains among the top trade partners, many European countries had been displaced by Asian or other Latin American economies (see Table 1).

This redirection of trade mirrors a higher degree of business cycle synchronization among emerging economies. De la Torre (2011) stress that whereas business cycles in Latin America countries and China have become increasingly correlated, they seem to have decoupled from the rich countries' cycles, a process that was particularly notorious with the unexpectedly fast recovery after the financial crisis of 2008. Nevertheless, direct trade linkages are not the only channel through which growth can be affected. As argued by Calderón (2009), indirect linkages, the effects through third countries that are also important trade partners, may be even stronger. Table 1 shows that China has become an important destination to Latin American exports as well as to exports of large industrialized economies: the Chinese share of American exports rose from 1.9 percent in 1991 to 9.0 percent in 2010, whereas the share of German exports increased from to 0.9 to 8.2 percent. These figures hint that, in the new world trade configuration, the influence of the Chinese economy on Latin America is likely to be manifested not only by stronger direct trade links, but also by indirect effects through its increasing importance for the region's traditional main trade partners.

The purpose of this paper is to investigate the implications of this new global scenario, where emerging markets – particularly China – are more prominent in the world economy, for Latin American growth. In particular, we aim to answer the following questions:

- How has Latin American growth responded to shocks to traditional trade partners like the United States and, to a lower extent, Germany? Have these responses changed by the emergence of China as a global actor?

- Are the healthy growth rates observed in Latin American during the 2000s a byproduct of the Chinese juggernaut? If so, were they due to a closer bilateral relationship with China or to second-round effects of China's boosting demand?

- Even though the Chinese economy is the most emblematic and sounding case of a large fast-growing emerging economy, the new global order has witnessed the emergence of others as well. For instance, Latin America is celebrating that Brazil has recently overtaken the United Kingdom as the world's sixth largest economy. But, does a shock to the Brazilian economy exert similar effects across the region than a shock to China? In other words, does a Brazilian shock have global impacts?

In order to answer these questions, following Abeysinghe and Forbes (2005), we estimate and simulate a structural VAR (SVAR) model for the growth rates of 29 countries around the globe, for the last two decades. To achieve a parsimonious yet dynamically rich specification, we constrained the feedback effects from a country's trade partners to its own growth rates by consider a "rest of the world" aggregate rather that each trade partner individually. Time-varying bilateral trade weights are used in the aggregation, and this enables us to explore how the complex interactions across the growth rates of the 29 countries in our sample has evolved through time. In particular, the SVAR model capture not only the direct effects of trade, but also indirect effects such that a shock to one country can have large effects on others, even if they are minor trading partners.

**Table 1.** *Export shares for Latin American (LA) and selected countries, 1991 and 2010*

| | United States | Germany | Brazil | China | Rest of Europe | Rest of LA | Rest of Asia | Others |
|---|---|---|---|---|---|---|---|---|
| **1991** | | | | | | | | |
| Argentina | 13.6 | 8.0 | 16.3 | 2.7 | 31.7 | 17.4 | 8.8 | 1.4 |
| Brazil | 26.0 | 8.8 | – | 0.9 | 26.3 | 17.1 | 17.9 | 2.9 |
| Chile | 21.2 | 9.4 | 5.9 | 1.1 | 25.8 | 8.5 | 27.1 | 1.1 |
| Colombia | 48.0 | 9.3 | 0.9 | 0.3 | 18.1 | 17.4 | 4.5 | 1.5 |
| Ecuador | 62.8 | 6.2 | 0.8 | 0.0 | 10.9 | 15.5 | 2.9 | 0.9 |
| Mexico | 83.8 | 1.3 | 0.5 | 0.0 | 6.1 | 1.9 | 3.6 | 2.9 |
| Peru | 26.8 | 6.6 | 3.9 | 5.7 | 23.6 | 14.4 | 16.5 | 2.5 |
| Uruguay | 11.8 | 10.1 | 28.3 | 7.4 | 18.2 | 17.5 | 5.1 | 1.6 |
| Venezuela | 70.7 | 5.2 | 2.9 | 0.0 | 8.0 | 6.4 | 4.2 | 2.5 |
| *LA Average* | *40.5* | *7.2* | *7.4* | *2.0* | *18.7* | *12.9* | *10.1* | *1.9* |
| United States | – | 6.3 | 1.8 | 1.9 | 21.8 | 13.5 | 26.7 | 28.0 |
| Germany | 9.5 | – | 0.7 | 0.9 | 76.7 | 1.9 | 8.2 | 2.0 |
| China | 10.0 | 3.8 | 0.1 | – | 6.5 | 0.5 | 77.2 | 1.9 |
| **2010** | | | | | | | | |
| Argentina | 7.0 | 3.5 | 27.6 | 11.1 | 16.4 | 22.3 | 8.7 | 3.3 |
| Brazil | 13.2 | 5.5 | – | 20.9 | 19.4 | 25.2 | 13.7 | 2.0 |
| Chile | 11.4 | 1.5 | 7.0 | 28.3 | 14.6 | 10.4 | 23.3 | 3.6 |
| Colombia | 50.9 | 0.8 | 3.1 | 5.9 | 13.9 | 18.2 | 5.5 | 1.7 |
| Ecuador | 45.9 | 2.4 | 0.4 | 2.5 | 11.8 | 31.6 | 4.6 | 0.6 |
| Mexico | 83.1 | 1.2 | 1.3 | 1.5 | 3.4 | 3.8 | 1.8 | 4.0 |
| Peru | 15.8 | 4.4 | 2.9 | 18.0 | 23.9 | 12.3 | 10.7 | 12.0 |
| Uruguay | 3.7 | 8.3 | 25.9 | 17.2 | 15.6 | 23.9 | 4.4 | 1.1 |
| Venezuela | 57.8 | 1.3 | 1.0 | 11.1 | 4.2 | 4.2 | 19.5 | 1.0 |
| *LA Average* | *32.1* | *3.2* | *8.7* | *12.9* | *13.7* | *16.9* | *10.2* | *3.3* |
| United States | – | 4.7 | 3.5 | 9.0 | 15.7 | 21.2 | 19.3 | 26.6 |
| Germany | 9.2 | – | 1.7 | 8.2 | 68.0 | 2.5 | 8.3 | 2.1 |
| China | 24.2 | 5.8 | 2.1 | – | 14.9 | 3.9 | 44.7 | 4.5 |

**Notes:** The export share for country *i* is computed as the ratio of exports from country *i* (row) to region or country *j* (column), to the sum of exports from country *i* to the 29 countries listed in section 3.1. The list is comprehensive but excludes Africa, Central America, the Middle East and Eastern Europe. The shares sum to 100 across rows.
**Source:** Direction of Trade Statistics (IMF).

The increase in globalization over the last 20 years has highlighted the importance and pervasiveness of international linkages in the world economy, and the importance of capturing those linkages in empirical macroeconomic models. Thus, there is a large literature in international economics exploiting such interrelationships. Early studies include Norrbin and Schlagenhauf (1996), Elliott and Fatas (1996), and more recently Abeysinghe and Forbes (2005), Canova (2005), Enders and Souki (2008) and Canova and Ciccarelli (2009). The most popular thread is related to the so-called global VAR (GVAR) advanced in Pesaran et. al. (2004) and extended in Dees et. al. (2007). Recently, Cesa-Bianchi et. al. (2011) have used the GVAR approach to answer questions similar to those formulated above.

Even though our modeling approach is related to the GVAR, there are some important methodological differences. Firstly, our model is smaller as it includes one variable per country (GDP growth). Even though this prevents us to label shocks more adequately (for instance, supply versus demand shocks), it allows us to formally test the aggregation hypothesis that is taken for granted in the GVAR literature. Secondly, our identification strategy differs in that we also use the aggregation restrictions to identify structural country specific shocks. Thirdly, we propose a standardized impulse response function that can be interpreted as an elasticity, in order to deal with the different variances of shocks across countries in the model. Finally, we exploit the aggregation restrictions further

to explore order and rank conditions for instrumental variable estimation. In this way, we do not need to rely on weak exogeneity assumptions, that every single country in the world – but the United States – is treated as a small open economy, that are ubiquitous in the traditional GVAR approach.

We find strong evidence that supports the increasing effects of China over Latin America's growth, in agreement with Cesa-Bianchi et. al. (2011). We also find weak but indicative evidence of diminishing effects of the United States and Germany. On the other hand, our results indicate that Brazilian shocks are qualitatively different to the Chinese ones, because its second-round effects are only important in a few neighboring countries. The results also point out to indirect effects of China's growth to explain the accelerating growth of most Latin America countries.

The remainder of the paper is organized as follows. Section 2 discusses methodological issues and develops an SVAR that allows for rich feedbacks parsimoniously. Furthermore, a formal hypothesis test on the aggregation restrictions, embedded in the SVAR, is proposed. Section 3 describes the data, presents time-varying impulse response functions, and analyzes the shifts in the effects of a shock originated in the United States, China, Germany and Brazil. Counterfactual simulations are also performed to quantify and disentangle the gains for Latin American countries of the new trade structure. Section 4 gives closing remarks and avenues for further research.

## 2 Methodological issues

This section discusses the econometric framework used to investigate how the feedbacks amongst the growth rates of $n$ countries around the globe have evolved in the last two decades. Two major points are considered. Firstly, aggregation restrictions are imposed into a standard, potentially large reduced form VAR of growth rates, and we formally test their significance. These restrictions not only promote parsimony but also identify a structural form and suggest valid and relevant instruments for estimation. Secondly, as in Abeysinghe and Forbes (2005) and Cesa-Bianchi et. al. (2011), we allow the bilateral trade weights to evolve through time, thereby capturing rich dynamics reflected in a changing direction in Latin American trade towards emerging markets. This feature allows us to compute time-varying impulse response functions.

### 2.1 The aggregation hypothesis

Our starting point is the reduced form VAR($p$) model

$$\boldsymbol{y}_t = \sum_{r=1}^{p} \boldsymbol{A}_r \boldsymbol{y}_{t-r} + \boldsymbol{\varepsilon}_t \,, \tag{1}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables whose $i$-th element corresponds to the growth rate of country $i$ in period $t$, $\boldsymbol{A}_r$ ($r = 1, 2, \ldots, p$) are coefficient matrices and $\boldsymbol{\varepsilon}_t$ is the vector of mutually correlated *iid* statistical innovations. The covariance matrix of $\boldsymbol{\varepsilon}_t$ is an $n \times n$ positive define matrix $\boldsymbol{\Omega}_\varepsilon$.

It is well-documented that the usefulness of a dynamic model like (1) may be limited in finite samples due to the proliferation of parameters that need to be estimated. Indeed, each additional lag implies the estimation of $n^2$ coefficients, and these may be poorly estimated with the sample sizes typically encountered in applications. Thus, promoting parsimony by imposing meaningful restrictions on matrices $\boldsymbol{A}_r$ is likely to improve the inferential content of testing procedures based on the VAR system. This is the purpose of aggregation restrictions, where given weights are used in the construction of aggregated variables that maintain feedback effects across countries.

Consider an aggregate composed by the $(n-1)$ variables in $\boldsymbol{y}_t$ other than $y_{i,t}$,

$$x_{i,t} = \sum_{j=1}^{n} w_{ij} y_{j,t} \qquad \text{where} \qquad \sum_{j=1}^{n} w_{ij} = 1 \qquad \text{and} \qquad w_{ii} = 0 \,. \tag{2}$$

The definition of the aggregate $x_{i,t}$ is general. The weights $w_{ij}$ may be time-varying, but to avoid cluttering the notation we leave this time dependence implicit (we relax this formulation below). Also, the weights $w_{ij}$ are constrained *not* to be estimated jointly with $\boldsymbol{A}_r$, otherwise the linearity in the VAR model may be lost with

aggregation. This situation corresponds to either non-random weights or stochastic weights that are predetermined, i.e. its determination (and so its estimation) is independent from $\boldsymbol{\varepsilon}_t$.

Take the $i$-th equation in the unrestricted VAR (1)

$$y_{i,t} = \sum_{r=1}^{p} a_{ii}(r) y_{i,t-r} + \sum_{r=1}^{p} \sum_{j \neq i}^{n} a_{ij}(r) y_{j,t-r} + \varepsilon_{i,t}, \tag{3}$$

where $y_{i,t}$ is the $i$-th element of $\mathbf{y}_t$, $\varepsilon_{i,t}$ is the $i$-th element of $\boldsymbol{\varepsilon}_t$, and $a_{ij}(r)$ denotes the $(i, j)$-th element of $\mathbf{A}_r$. In an alternative, restricted model all dynamic feedback to $y_{i,t}$ come from its own lags and lags of the aggregate,

$$y_{i,t} = \sum_{r=1}^{p} a_{ii}(r) y_{i,t-r} + \sum_{r=1}^{p} c_i(r) x_{i,t-r} + \bar{\varepsilon}_{i,t} = \sum_{r=1}^{p} a_{ii}(r) y_{i,t-r} + \sum_{r=1}^{p} \sum_{j \neq i}^{n} c_i(r) w_{ij} y_{j,t-r} + \bar{\varepsilon}_{i,t}. \tag{4}$$

If $a_{ij}(r) = c_i(r) w_{ij}$, then the restricted model (4) is equivalent to the model without restrictions (3). These $p(n-1)$ equalities imply a total of $p(n-1) - p = p(n-2)$ restrictions that take the form

$$a_{ij}(r) - \left[ \frac{w_{ij}}{w_{ik}} \right] a_{ik}(r) = 0 \qquad \text{for} \quad j \neq k, \, k \neq i \quad \text{and} \quad r = 1, 2, \ldots, p. \tag{5}$$

Thus, the aggregation restrictions imply that the non-diagonal elements of the $i$-th row of $\mathbf{A}_r$ are proportional to each other, and the proportionality factor is given by the ratio $w_{ij}/w_{ik}$. In other words, $y_{j,t}$ and $y_{k,t}$ affect the expected value of future realizations of $y_{i,t}$ proportionally to their contributions to the aggregate (2).

The unrestricted model is obtained by regressing $y_{i,t}$ on the $p$ lags of $\mathbf{y}_t$. This amounts to $pn$ coefficients per equation and $pn^2$ in the entire VAR. On the other hand, in the restricted model $y_{i,t}$ is regressed on its $p$ lags and the $p$ lags of the aggregate $x_{i,t}$. Here, each equation has $2p$ coefficients and the restricted VAR has $2pn$ coefficients. Thus, the aggregation restrictions can reduce the number of coefficients to be estimated substantially, even for moderate values of $n$. For instance, if $p = 2$ and $n = 10$ then we have $pn^2 = 200$ coefficients in the unrestricted model, and only $2pn = 40$ in the restricted, a total of $np(n-2) = 160$ restrictions.

The aggregation restrictions can be conveniently reinterpreted as exclusion restrictions, and this is the basis for hypothesis testing. After simple manipulations, the original equation (3) can be rewritten as

$$y_{i,t} = \sum_{r=1}^{p} a_{ii}(r) y_{i,t-r} + \sum_{r=1}^{p} c_i(r) x_{i,t-r} + \sum_{r=1}^{p} \sum_{j \neq i}^{n} \delta_{ij}(r) y_{j,t-r} + \varepsilon_{i,t}, \tag{6}$$

where $\delta_{ij}(r) = a_{ij}(r) - c_i(r) w_{ij}$ for $r = 1, \ldots p$, $j = 1, 2, \ldots, n$ and $j \neq i$. Therefore, the restricted model has $\delta_{ij}(r) = 0$ for all $r$ and $j \neq i$. Thus, testing the aggregation hypothesis amounts to estimate the extended equation (6) via OLS and testing $H_0 : \delta_{ij}(r) = 0$ using a standard Wald statistic. Note that $H_0$ has the appealing interpretation that once $x_{i,t}$ is controlled for, its constituents $y_{j,t}$ have no predictive power on $y_{i,t}$.

## 2.2 The structural model

Even though the reduced form is used to investigate whether a constrained model based on aggregation restrictions serves as a valid characterization of the data, the ultimate object of interest is a model that allows a contemporaneous feedback from $x_{i,t}$ to $y_{i,t}$. In econometric jargon, we seek a structural form (SVAR) associated to the reduced form (1), after imposing the aggregation restrictions. The $i$-th equation of such structural model is

$$y_{i,t} = \sum_{r=1}^{p} \phi_i(r) y_{i,t-r} + \sum_{r=0}^{p} \beta_i(r) x_{i,t-r} + u_{i,t}, \tag{7}$$

where $u_{i,t}$ is a structural shock to the $i$-th county growth rate. To express the system in matrix form, define $\mathbf{B}_r = \text{diag}(\beta_1(r), \beta_2(r), \ldots, \beta_n(r))$ and $\boldsymbol{\Phi}_r = \text{diag}(\phi_1(r), \phi_2(r), \ldots, \phi_n(r))$ as the $n \times n$ diagonal matrices that collect

the coefficients associated to the $r$-th lag effects. Define also $W_t$ as the $n \times n$ matrix whose $(i, j)$ element is $w_{ij,t}$, and recall that $w_{ii,t} = 0$ for all $t$. Then, upon stacking all $n$ equations of the form (7), we obtain

$$(I_n - B_0 W_t) y_t = \sum_{r=1}^{p} (\Phi_r + B_r W_{t-r}) y_{t-r} + u_t. \tag{8}$$

The consequences of imposing aggregation restrictions can be clearly appreciated in the SVAR (8), where the $n \times n$ feedback matrix $\Phi_r + B_r W_{t-r}$ contains only $2n$ unknown parameters, and the $n \times n$ matrix of contemporaneous effects $I_n - B_0 W_t$, which is similar to that in Elliott and Fatas (1996), contains only $n$ free parameters. Therefore, unlike the SVAR tradition where the structural form – especially its contemporaneous effects and the covariance matrix of the structural shocks – needs to be restricted in order to achieve identification, the aggregation restrictions solely identify the model: whereas the reduced form contains $pn^2$ free parameters, the structural has only $n(2p + 1)$, so that identification is achieved under the mild condition that $p(n - 2) \geq 1$.[1] Importantly, identification follows from the fact that $W_t$ is predetermined, i.e. its estimation is independent from the estimation of the SVAR.

Another interesting feature of (8) is that it is a time-varying SVAR. As such, it has the flexibility of stabilizing the estimates of the time invariant coefficients ($B_r$ and $\Phi_r$) in the presence of major shocks, such as international crises. By construction, changes in the historical bilateral trade structures through time will be reflected in all relationships involved in the SVAR, either indirect and direct, contemporaneous or lagged. Moreover, since $W_t$ is likely to evolve smoothly, so will the coefficients in (8), a result that is usually enforced by letting them follow correlated random walks, a favorite specification in time-varying VARs (cf. Primiceri, 2005). Nevertheless, since the changing nature of the model parameters is linked to the evolution of the predetermined weights $W_t$, the treatment of their stochastic properties is greatly simplified (see, for instance, section 2.4).

## 2.3 Impulse response analysis

The time-varying nature of the coefficient matrices in (8) imply that functions of these matrices, such as the impulse response function, also depend on $t$. This is an interesting property of the model and allows us to investigate how different configurations of the $W_t$ matrices (different trade structures) affect the dynamic responses of the system.

*Conditional on a particular trade configuration $W_t = W$* for all $t$, the SVAR becomes time invariant and can be given the moving average representation

$$y_t = \Theta_0 u_t + \Theta_1 u_{t-1} + \Theta_2 u_{t-2} + \Theta_3 u_{t-3} + \dots. \tag{9}$$

The matrices $\Theta_h$ satisfy the recursion

$$\Theta_h = C_1 \Theta_{h-1} + C_2 \Theta_{h-2} + \dots + C_p \Theta_{h-p}, \tag{10}$$

with $\Theta_0 = C_0$ and $\Theta_h = 0$ for $h < 0$ as initial conditions, and $C_0 = (I_n - B_0 W)^{-1}$ and $C_r = C_0(\Phi_r + B_r W)$ (the dependence on $W$ is left implicit to alleviate the notation). The responses to a structural shock after $h$ periods are given by the elements of $\Theta_h$. The accumulated responses are collected in $\Psi_h = \Theta_0 + \Theta_1 + \dots + \Theta_h$.

Following Winkelried (2011), to compare the effects of shocks of different sizes amongst countries, we entertain a standardized response that takes into account the relative variability of the different shocks in $u_t$. Let $e_i$ be a $n \times 1$ selection vector with unity as its $i$-th element and zeros elsewhere. Suppose we perturb the $i$-th element of $u_t$ ($u_0 = e_i$), a shock that is interpreted as a structural perturbation to the $i$-th country's growth rate. The *relative effect of shock $i$ on country $j$ after $h$ periods* is given by

$$\rho_{ij}(h) = \frac{e_j' \Psi_h e_i}{e_i' \Psi_h e_i}. \tag{11}$$

After $h$ periods, the structural shock has an accumulated effect of $e_i' \Psi_h e_i$ on the $i$-th country's growth rate. Thus, given the linearity of (9), setting $u_0 = e_i/(e_i' \Psi_h e_i)$ renders a shock that produces an increase in the $i$-th growth rate

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of exactly one percent after $h$ periods. The definition of (11) is simply the cumulative response of the growth rate of country $j$ to such a shock, i.e. how much of the shock to the $i$-th perturbation passes through the $j$-th growth rate.

The relative effects summarize complicated dynamics in the SVAR. The impact effects $\rho_{ij}(0)$ can be regarded as a *direct response* to the shock, transmitted immediately, and depends heavily on the bilateral relationship between countries $i$ and $j$, in particular on the weight $w_{ji}$. On the other hand, further effects $\rho_{ij}(h)$ for $h > 0$ include the influence of the shock being propagated to other economies in the system. Thus, for $h > 0$ the relative effects are *indirect multipliers*. Due to these multipliers, a shock to one country can have large effects on others even if they are minor trading partners.

Finally, it is worth mentioning that whereas our model permits the identification of the *origin* of the shock (i.e., country $i$), it is essentially silent on deeper explanations related to its source (i.e., whether it is a demand or supply shock). Hence, we do not attempt to give the shock an interpretation other than the economy it hits first (see Enders and Souki, 2008, for further discussion).

## 2.4 Estimation

Let $x_t = W_t y_t$ be the $n \times 1$ vector of aggregates: the $i$-th element of $x_t$ is $x_{i,t}$. Then, (8) can be written as

$$y_t = \sum_{r=1}^{p} \Phi_r y_{t-r} + B_0 x_t + \sum_{r=1}^{p} B_r x_{t-r} + u_t, \tag{12}$$

which resembles the GVAR formulation of Pesaran et. al. (2004). This representation suits nicely the estimation of $B_0$, $B_r$, $\Phi_r$ and $\Omega_u$, the covariance matrix of $u_t$. System (12) corresponds to a standard simultaneous equations system where, given the definition of $x_t$ and the possible correlations among the elements of $u_t$, $x_t$ can be regarded as endogenous. The aggregation restrictions not only help identifying the SVAR model, but also suggest the use of lagged growth rates as instrumental variables. With this, we avoid invoking usual weak exogeneity assumptions on $x_t$ that have been questioned in Mutl (2009).

As mentioned, it turns out that the lags of $y_t$ provide valid and relevant instrumental variables for the estimation of (12). This is a consequence of each element of $x_t$ being defined as a particular linear combination of $y_t$, hence the information contained in $y_t$ that lie outside the span of $W_t$ can be used to identify the model.

To illustrate the relevance of $y_{t-1}$ as a vector of instruments, consider the first structural equation in the case where $n = 3$ and $p = 1$, and let $\mathbf{w}_t$ designate the first row of $W_t$. Then, the regressors are $(y_{1,t-1}, x_{1,t}, x_{1,t-1})' \equiv (\mathbf{e}_1' y_{t-1}, \mathbf{w}_t y_t, \mathbf{w}_{t-1} y_{t-1})'$, so the expected value of the outer product of the vectors of regressors and instruments is the $3 \times 3$ matrix

$$Q = \begin{bmatrix} \mathbf{e}_1' \mathbb{E}(y_{t-1} y_{t-1}') \\ \mathbf{w}_t \mathbb{E}(y_t y_{t-1}') \\ \mathbf{w}_{t-1} \mathbb{E}(y_{t-1} y_{t-1}') \end{bmatrix}.$$

Since $\mathbf{w}_t \mathbf{e}_1 = 0$ by construction for all $t$, the first row of $Q$ is linearly independent from the second and the third ones as long as $\mathbb{E}(y_t y_{t-1}') \neq \mathbf{0}$. On the other hand, if $\mathbb{E}(y_t y_{t-1}') \neq \mathbb{E}(y_{t-1} y_{t-1}')$, then the second and third rows are also independent even if there is not time-variation in $\mathbf{w}_t$. Thus, rank$(Q) = 3$ under very mild conditions and so $y_{t-1}$ constitutes a vector of relevant instruments satisfying the rank condition for identification. Further lags of $y_t$ overidentify the model.[2]

Then, a standard equation-by-equation two stage least squares procedure featuring lags $y_{t-1}, \ldots, y_{t-K}$ as instruments for every equation is used to estimate (12). The results were robust to the choice of $K \geq p$, and also to the usage of alternative estimation methods such as system-wise three stage least squares. Given the results on $p$ in Table 2 below, we set $K = 4$.

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[2] "First stage regressions" suggest that the instruments are of acceptable quality. The adjusted $R^2$ of the regressions of $x_{i,t}$ on $y_{t-1}$ ranges from 0.19 to 0.54 with mean and median values of around 0.42. These figures may be further improved by including additional lags of $y_t$ as regressors. For instance, the adjusted $R^2$ of the regressions of $x_{i,t}$ on $y_{t-1}$ and $y_{t-2}$ ranges from 0.23 to 0.59.

# 3 Results

Next we present the main results of our empirical analysis. First, the data and sources of information are described. Then, we find supporting evidence of the aggregation hypothesis. The structural model is then estimated and the evolution of its impulse response function is analyzed. It is found that the influence of the Chinese economy on Latin American countries, except Venezuela, has significantly increased. The higher influence reflects both a closer bilateral relationship with China, and more importantly, the consequences of a higher Chinese growth worldwide. Furthermore, the results also point out that the influence of the traditionally important trade partners, such as the United States and Europe (precisely, Germany), has decreased in the same period. However, the evidence for the last phenomenon is weak and we take the results as indicative rather than categorical.

## 3.1 Data

We have assembled a comprehensive database of quarterly real gross domestic product (GDP) growth rates, from 1989Q1 to 2011Q2, which consists of $n = 29$ series: 9 from Latin America (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Uruguay and Venezuela), 2 from North America (United States and Canada), 8 from Europe (France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland and United Kingdom), 8 from Asia (Hong Kong, India, Japan, Mainland China, Malaysia, Singapore, South Korea and Thailand), and 2 from Oceania (Australia and New Zealand). The main criterion for including a country in the database is data availability. For the sample period, these countries represent more than 80 percent of world production, and more than 80 percent of global trade.

Our main source of information is the *International Financial Statistics* (IFS) database, which contains information for most of the countries for all the sample period. For many Latin American countries (Argentina, Brazil, Colombia, Ecuador and Uruguay) the IFS record is incomplete and data from each country's central bank is used for the missing periods, whereas for Venezuela the entire series come from its central bank. In the case of Thailand and Mainland China, the data are completed with computations from Abeysinghe and Gulasekaran (2004), available at Tilak Abeysinghe's website. The IFS data for the North American, European and Oceanian countries are seasonally adjusted. Unadjusted series were seasonally adjusted using an automatic TRAMO-SEATS procedure.

Trade data were obtained from the *Direction of Trade Statistics* (DOTS) database from 1989 to 2010. Exports are reported as freight-on-board (fob) in US dollars. For each year, the export weight $w_{ij}$ is computed as the ratio of exports from country $i$ to country $j$, to the sum of exports from country $i$ to the 29 countries in the sample. Then, we arrive at quarterly figures by taking a 12 quarter moving average to the step-like series obtained by repeating annual figures in every quarter of the corresponding year. Finally, in order to ensure these weights to be predetermined, they are lagged 4 quarters, i.e. the weights of 2011Q1 correspond to the trade structure of 2010Q1. All in all, the dataset consists of $n(n-1) = 812$ export weight series (recall that $w_{ii} = 0$).[3]

## 3.2 The aggregation hypothesis

Given the limited amount of data, about 85 observations after adjusting for initial conditions, we are not able to test the aggregation hypothesis discussed in section 2.1 for all available trade partners ($n - 1 = 28$). However, a casual inspection of the data reveals that for a typical country a significant share of trade is concentrated in a considerably smaller number of partners. Thus, we set $n$ as the minimum value such that the average share of the main $n$ trade partners (through time) is at least 70 percent of the trade with the 29 countries in the sample. For the aggregation test to make sense, $n > 2$ is required. Table 2 shows that an average of 5 trade partners are considered with Mexico, Canada and Venezuela at one end ($n = 3$), and Brazil, Chile and Peru at the other ($n \geq 8$).

An important practical issue is the determination of the lag length $p$, which is made on an equation-by-equation basis. For each country, we choose the value of $p = \{1, 2, \ldots, 6\}$ that minimizes a modified Akaike information criterion ($\text{AIC}_c$). For a sample size of $T$ observations and a equation with $K$ regressors, this criterion is defined as $\text{AIC}_c = \text{AIC} + 2K(K+1)/(T-K-1)$, where AIC is the usual Akaike information criterion (see Hurvich and Tsai, 1989). $\text{AIC}_c$ provides a second-order bias correction to AIC by adding a penalty term that can be substantial in

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[3] It is worth mentioning that the results using trade weights (exports plus imports) were similar to those reported below. In addition, the conclusions are unaltered when using 8 quarter moving averages of yearly figures as estimates of the quarterly weights data.

**Table 2.** *Testing for aggregation*

| | $n$ | $\sum w$ | $p$ | df | $\chi^2$ statistic | $p$-value |
|---|---|---|---|---|---|---|
| Argentina | 7 | 71 | 1 | 5 | 2.888 | 0.717 |
| Brazil | 8 | 71 | 1 | 6 | 7.012 | 0.320 |
| Chile | 9 | 74 | 1 | 7 | 11.722 | 0.110 |
| Colombia | 4 | 71 | 1 | 2 | 0.842 | 0.656 |
| Ecuador | 4 | 70 | 4 | 8 | 15.261 | 0.054* |
| Mexico | 3 | 91 | 2 | 2 | 4.037 | 0.133 |
| Peru | 8 | 70 | 4 | 24 | 30.816 | 0.159 |
| Uruguay | 7 | 73 | 1 | 5 | 12.126 | 0.033** |
| Venezuela | 3 | 77 | 1 | 1 | 0.666 | 0.414 |
| United States | 7 | 70 | 2 | 10 | 13.391 | 0.203 |
| Canada | 3 | 91 | 1 | 1 | 0.998 | 0.318 |
| France | 5 | 73 | 1 | 3 | 4.956 | 0.175 |
| Germany | 6 | 72 | 4 | 16 | 26.643 | 0.046** |
| Italy | 5 | 73 | 1 | 3 | 2.205 | 0.531 |
| Netherlands | 4 | 76 | 1 | 2 | 9.318 | 0.009*** |
| Spain | 4 | 73 | 2 | 4 | 9.064 | 0.060* |
| Sweden | 6 | 73 | 1 | 4 | 6.262 | 0.180 |
| Switzerland | 5 | 70 | 1 | 3 | 6.174 | 0.103 |
| United Kingdom | 6 | 75 | 1 | 4 | 6.783 | 0.148 |
| Hong Kong | 4 | 77 | 1 | 2 | 9.482 | 0.009*** |
| India | 7 | 71 | 1 | 5 | 5.079 | 0.406 |
| Japan | 6 | 71 | 1 | 4 | 2.183 | 0.702 |
| Mainland China | 4 | 71 | 3 | 6 | 8.024 | 0.236 |
| Malaysia | 6 | 74 | 1 | 4 | 9.217 | 0.056* |
| Singapore | 6 | 72 | 1 | 4 | 9.333 | 0.053* |
| South Korea | 5 | 70 | 1 | 3 | 3.829 | 0.280 |
| Thailand | 6 | 72 | 4 | 16 | 12.310 | 0.722 |
| Australia | 6 | 70 | 1 | 4 | 13.066 | 0.011** |
| New Zealand | 5 | 71 | 1 | 3 | 6.444 | 0.092* |

**Notes:** Results for $H_0 : \delta_{ij}(r) = 0$ in equation (6), for all $i = 1, \ldots, n$, $j \neq i$ and $r = 1, \ldots, p$. $n$ is the number of trade partners used to construct the aggregate $x$; $\sum w$ is the share of trade with of each country with its $n$ main partners; $p$ is the lag length chosen by a Modified Akaike criterion; df is the number of restrictions, $p(n - 2)$. *(**)[* * *] denotes rejection at a 10(5)[1] percent significance level.

applications like ours. This way, $AIC_c$ deals with the common critique that AIC tends to favor overparameterized models in small samples, while maintaining its desirable properties as a model selection device. Indeed, we observe in Table 2 that $AIC_c$ selects rather parsimonious specifications: in most of the equations, $p = 1$; Mexico, United States and Spain have $p = 2$, China has $p = 3$, and Ecuador, Peru, Germany and Thailand have $p = 4$.

Under the null hypothesis of aggregation ($\delta_{ij}(r) = 0$ in equation (6) for all $i = 1, \ldots, n$, $j \neq i$ and $r = 1, \ldots, p$), the standard Wald statistic is asymptotically distributed as $\chi^2$ with $p(n - 2)$ degrees of freedom. It can be seen in Table 2 that the aggregation hypothesis cannot be rejected in most of the cases (19 out of 29) at a 10 percent significance level. Moreover, in 8 of the remaining cases the rejection of the null is not particularly strong, in the sense that $H_0$ cannot be rejected at a 5 percent (5 cases) or at a 1 percent (3 cases) significance level. Only in two cases (Hong Kong and the Netherlands), the aggregation hypothesis is rejected at a 1 percent significance level. We take these results as supporting evidence that the restricted model, which uses trade weighted aggregates to summarize feedback effects from the rest of world, is capable to capture the main features of the data. The next step, thus, is to investigate the dynamics of the restricted global model.

## 3.3 Time varying effects of shocks around the globe

In order to quantify the transmission of external shocks to Latin American countries, and how it has changed from the beginning of the 1990s to the late 2000s, we conduct impulse response analyses conditional on different configurations of world trade (i.e., different matrices $W_t$). Amongst the 29 possible shocks of the system, 4 are of particular interest. The United States and countries of the Eurozone have been traditionally the main destinations of Latin American exports, and thus it is natural to consider a shock in the United States and a shock in Germany, as a representative of the Eurozone. On the other hand, one of the main focus of our empirical exploration is a shock to the new starring actor on the world trade scene: China. Finally, it is also of interest to enquiry whether a shock to the largest Latin American economy, Brazil, may have potential global impacts.

In a first exercise we compute the relative effects $\rho_{ij}(h)$ of a shock on the aforementioned countries at both ends of our sample: 1991 and 2011. Figure 1 depicts the relative effects as a function of $h$ for both periods, with confidence intervals constructed using a parametric bootstrap. There are some results to highlight:

- As expected, shocks to the United States and, to a lower extent, to Germany induce significant strong responses in all Latin American countries. Also, these effects have changed little from 1991 to 2011: even though point estimates are smaller in 2011 than in 1991, often the confidence intervals at the two different periods overlap, thus suggesting that the difference is not statistically significant. However, the effect of an American shock appears to be diminished significantly in the case of Chile, Ecuador and Peru, whereas the effect of a German shock is weaker in the case of Chile.

- Our estimations point out to a clear, significant increase in the influence of the Chinese shock in the region, in agreement with Cesa-Bianchi et. al. (2011). In all countries, but Venezuela, and for all $h$, the profile of the relative effects of the Chinese shock is significantly greater in 2011 than in 1991. The effect on impact ($h = 0$), which captures the changes in trade in the last two decades, has doubled, whereas the multiplier effects ($h > 0$) which include second-round effects of China as a global actor, has almost tripled. Furthermore, the results indicate that in 1991 the effects of a shock in China on Latin American were due exclusively to their trading links (the response on impact is not statistically different from the response after $h$ quarters), whereas in 2011 both the response on impact and the second-round effects increased unambiguously.
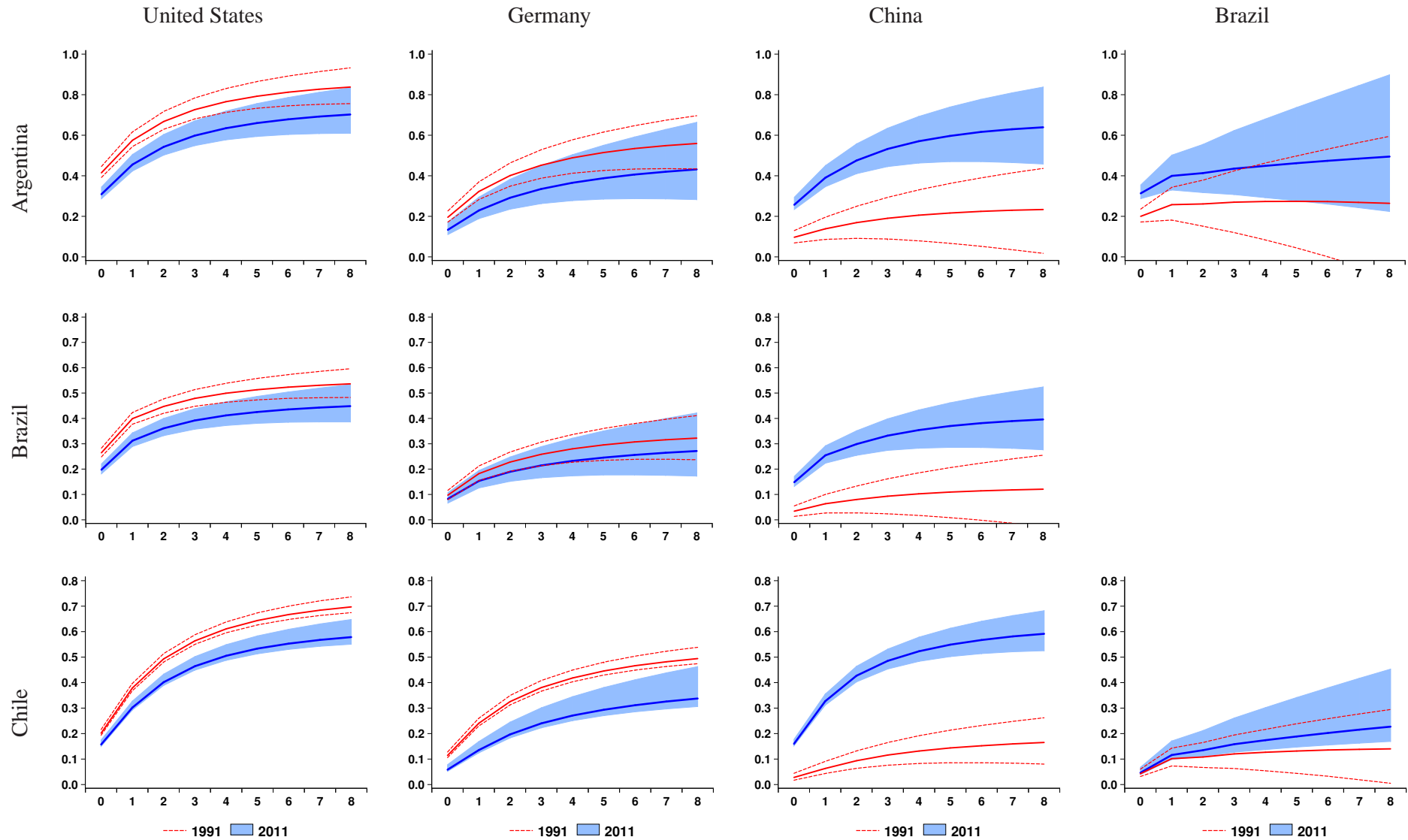
    It can be appreciated that in 1991 the effects of the German shock had been statistically higher than that of the Chinese shock. Two decades later, in 2011, the relative effect of the Chinese shock is of comparable magnitude to that of the German shock. Moreover, the point estimates of the former appear to be higher than the latter, even though the differences are not yet statistically significant.

- The Brazilian shock exerts an important influence on Argentina and Uruguay, the two countries in our sample that apart from Brazil are members of the Mercosur trading bloc. In the rest of Latin American countries, however, the effects of the Brazilian shock is comparably limited. In particular, the effect on impact ($h = 0$) does not seem different from the multiplier effects ($h > 0$), which suggest that the Brazilian shock, as opposed to the Chinese one, does not have global impacts. These results have not changed between 1991 and 2011.

In a second exercise we compute the relative effects for all quarters in the sample, to enquiry whether the documented changes in the influences of various shock on Latin American growth have evolved smoothly and monotonically. Figure 2 shows the resulting time profiles for selected values of $h = \{0, 1, 4, 8\}$. Recall that the direct effect of the shock is on impact, the first solid line $h = 0$, and as we move through the lines representing higher values of $h$ the responses are also influenced by the global effects generated by the shock.
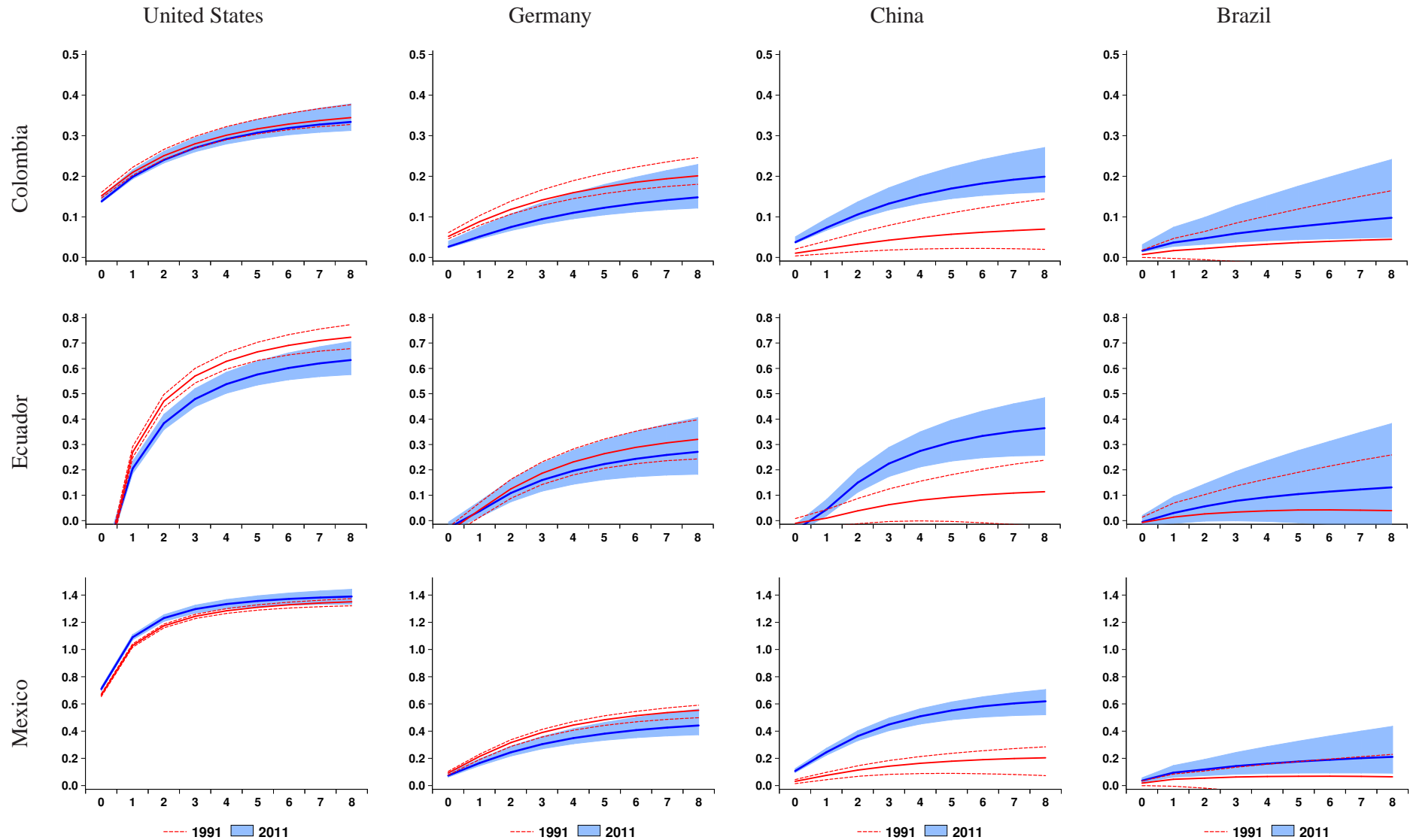
- The results on the Chinese shock are again worth commenting on. The effect on impact has shown a sustained upward trend since the mid 2000s, which mirrors the increase in bilateral trade with China for each country in Table 1. More interestingly, it is the second-round effects ($h > 0$) that display a steeper increase since the beginning of the 2000s, thereby capturing the importance of the Chinese shock worldwide. A tentative conclusion is that, even though China has become one of the main trade partners of Latin American countries, it is the indirect effect of an expansion in China what affects Latin American growth the most.

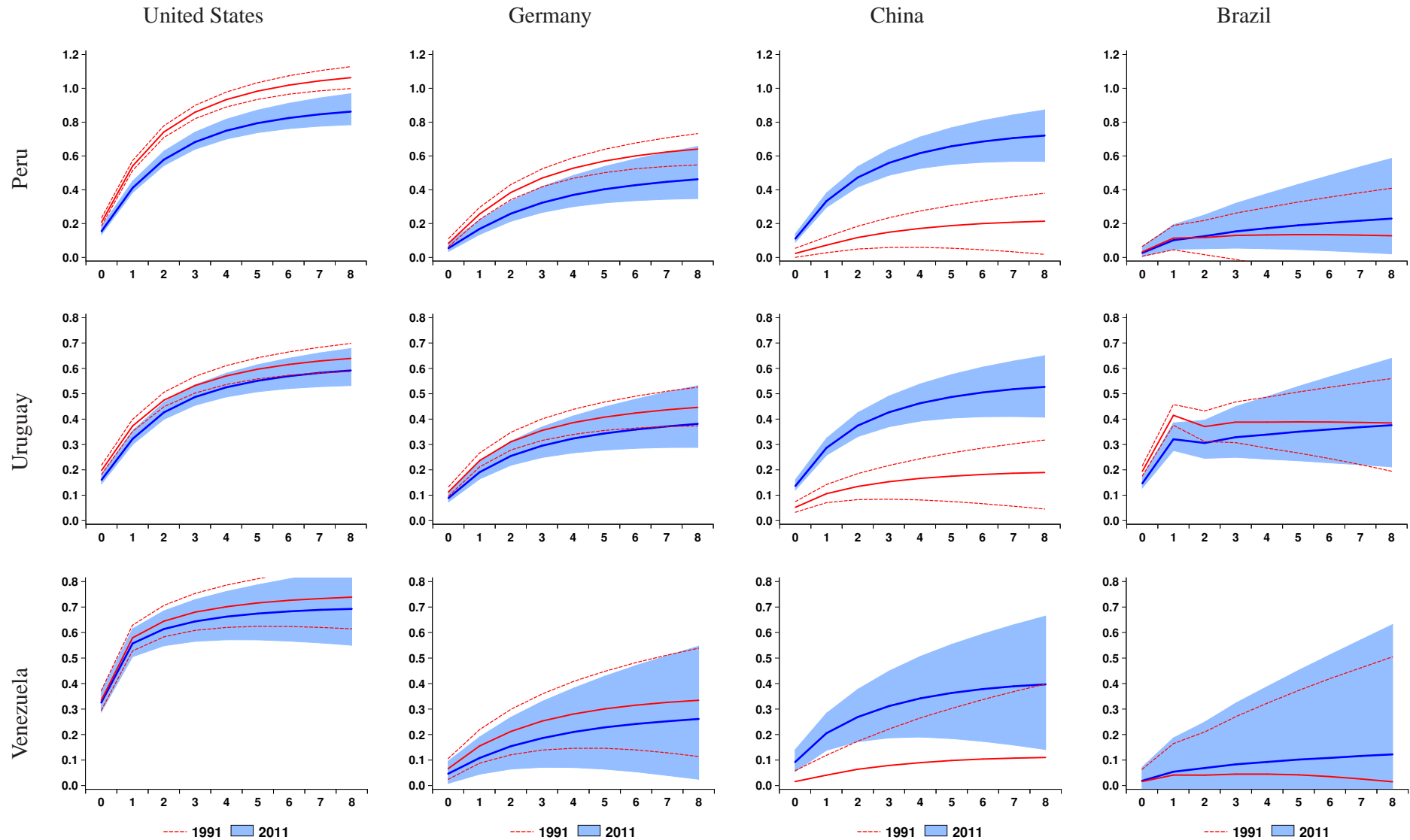**Figure 1.** *Relative effects of foreign shocks in Latin America: 1991 vs. 2011*



**Notes:** Each graph shows the relative effect of a shock in country $i$ (column) on country $j$ (rows), as a function of $h$ (horizontal axis) and for two configurations of the trade matrix $W_t$. See equation (11). Bootstrap 90 percent confidence intervals are shown as shaded areas for 2011, and 90 percent confidence bounds are shown as dashed lines for 1991. The scale of the vertical axis may vary across rows.

**Figure 1 (cont'd).** *Relative effects of foreign shocks in Latin America: 1991 vs. 2011*

**Notes:** Each graph shows the relative effect of a shock in country $i$ (column) on country $j$ (rows), as a function of $h$ (horizontal axis) and for two configurations of the trade matrix $W_t$. See equation (11). Bootstrap 90 percent confidence intervals are shown as shaded areas for 2011, and 90 percent confidence bounds are shown as dashed lines for 1991. The scale of the vertical axis may vary across rows.

**Figure 1 (cont'd).** *Relative effects of foreign shocks in Latin America: 1991 vs. 2011*

**Notes:** Each graph shows the relative effect of a shock in country $i$ (column) on country $j$ (rows), as a function of $h$ (horizontal axis) and for two configurations of the trade matrix $W_t$. See equation (11). Bootstrap 90 percent confidence intervals are shown as shaded areas for 2011, and 90 percent confidence bounds are shown as dashed lines for 1991. The scale of the vertical axis may vary across rows.

The time profile of the relative effects also uncovers interesting dynamics in the responses to the Chinese shock. For $h > 0$, its influence declines from 1998 to 2002, whereas the direct effect in $h = 0$ remains stable. This combination seems to be a consequence of the 1997 Asian financial crisis. Whereas it barely changed the bilateral relationships of Latin American countries with China, it hit hardly many of China's main trade partners. Hence, the trade amongst Asian economies shrunk and this phenomenon weakened the channel whereby shocks in China's growth were propagated around the globe (see Abeysinghe and Forbes, 2005).

- On the other hand, we observe that in the case of the American shock, the relative effects both on impact and indirect have remained mostly unchanged. However, the responses of Argentina, Chile, Peru and Uruguay after the 2008 financial crisis, reflect not only a modest shrinkage in the trade share of the United States, but more importantly somehow weaker second-round effects of an American shock.

  As concluded in the analysis of Figure 1, many of these changes are not statistically significant; nonetheless, if the movements observed by the end of the sample are an indication of a downward trend developing, it will not be long until a significant reduction in the importance of the American shock can be reported. In fact, this is the case of the responses to the German shock whose influence has shown a steady (albeit modest) decline since the mid 1990s, and for all the Latin American countries in the sample.

- Finally, the relative effects of a Brazilian shock display a hump between the mid 1990s to the mid 2000s, which is very pronounced for Mercosur members but is buffered for the remaining Latin American countries (notably Chile, that have important direct trade linkages with Mercosur economies). Outside Mercosur, however, the relative effects of a Brazilian perturbation are basically reflected by the direct impacts on trade, their second-round effects seem insignificant and very stable through time.

## 3.4   Direct vs. indirect effects: Counterfactual simulations

Our previous results point out to two important conclusions. Firstly, the changing trading structure of Latin American countries has promoted growth as it was oriented towards fast-growing economies, remarkably China. Secondly, second-round effects of the outstanding Chinese growth in the 2000s has constituted a relevant source of growth in the region.

Unfortunately, with the exception of the relative effects (11) on impact ($h = 0$), for $h > 0$ the analysis so far does not disentangle the direct effect of changing the trade structure from the indirect ones. Next, we perform counterfactual simulations in order to have a better grasp of the relative importance of these effects. In particular, using the actual estimated structural shocks $u_t$, the SVAR is simulated for the period 2006 to 2011 (the 2008 financial crisis occurred in the middle of this window), under different assumptions regarding the world trade structure, see equation (9):

- First, for all $t$ in the simulation window, the matrix $W_t$ is set equal to its average value over that period ($W_2$).

  The result is a set of growth rates that are close, but greater than the actual values. Compare the first and sixth columns of Table 3: an average of 5.51 percent versus and 4.94 percent. The reason for this discrepancy is that, in the simulations, although the upward trending export weights of Latin American countries with booming emerging markets are replaced with greater shares at the beginning of the simulation and with smaller shares by the end, the effects on growth are not compensated because of more favorable initial conditions. Therefore, the counterfactual set, i.e. the sixth column of Table 3, is used as a baseline scenario for comparative purposes.

- Second, the trade matrix $W_t$ is replaced by its average value over 1994 to 2000 ($W_1$).

  This situation corresponds to a trade structure before China's emergence as a global actor, and the results are given in the second column of Table 3. On average, Latin American growth amounts to a modest 2.94 percent, almost half of the growth obtained in the baseline scenario. The difference between scenarios (2.57 percent) gives the overall effect of the changing trade structure on growth, and is reported in the fifth column of Table 3.
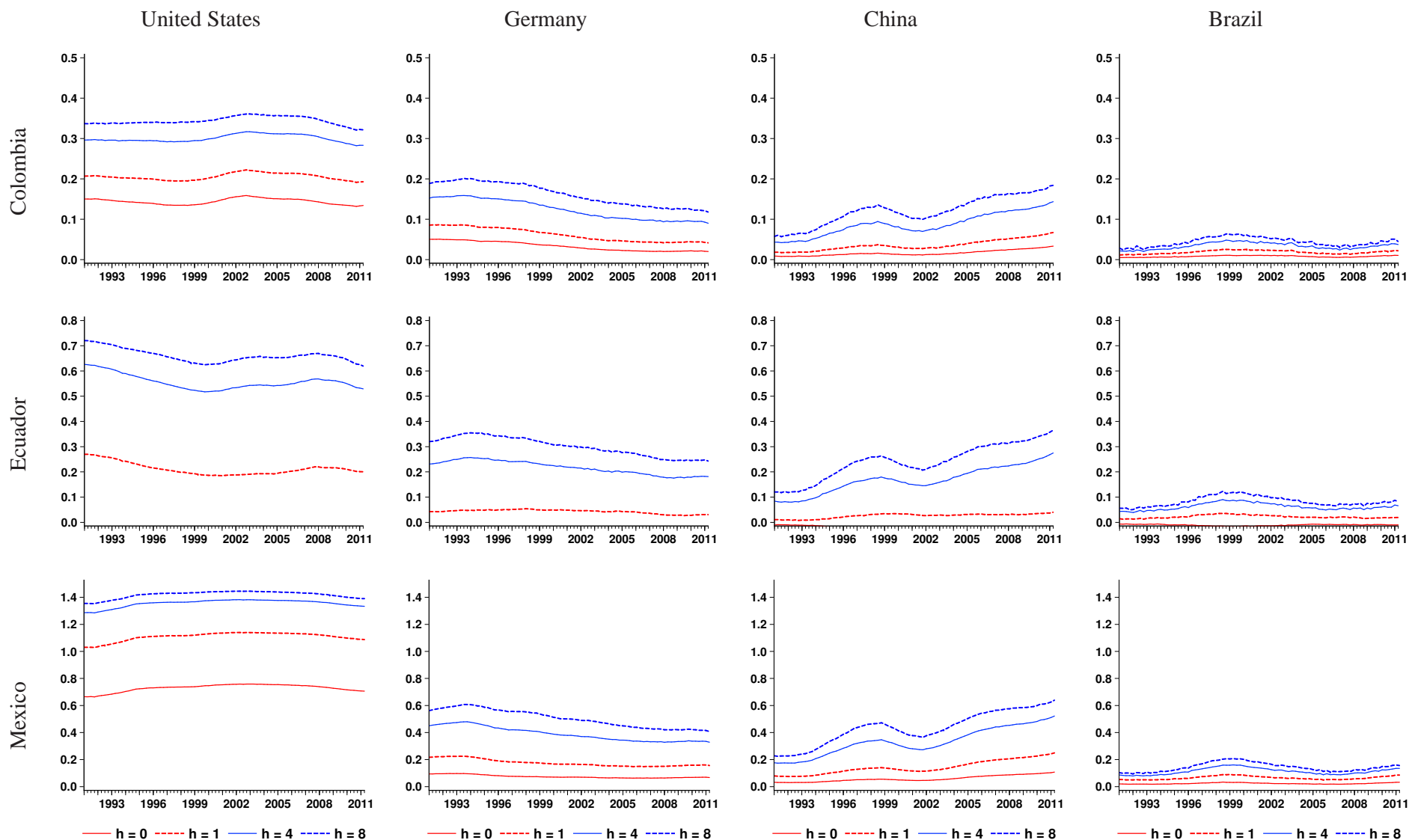
- Finally, an intermediate configuration is considered in order to assess the direct effects of the new trade structure on growth ($W_3$). The idea is to let Latin American's trade structure evolve, while keeping the

**Figure 2.** *Time profile of relative effects of foreign shocks in Latin America: 1991 to 2011*
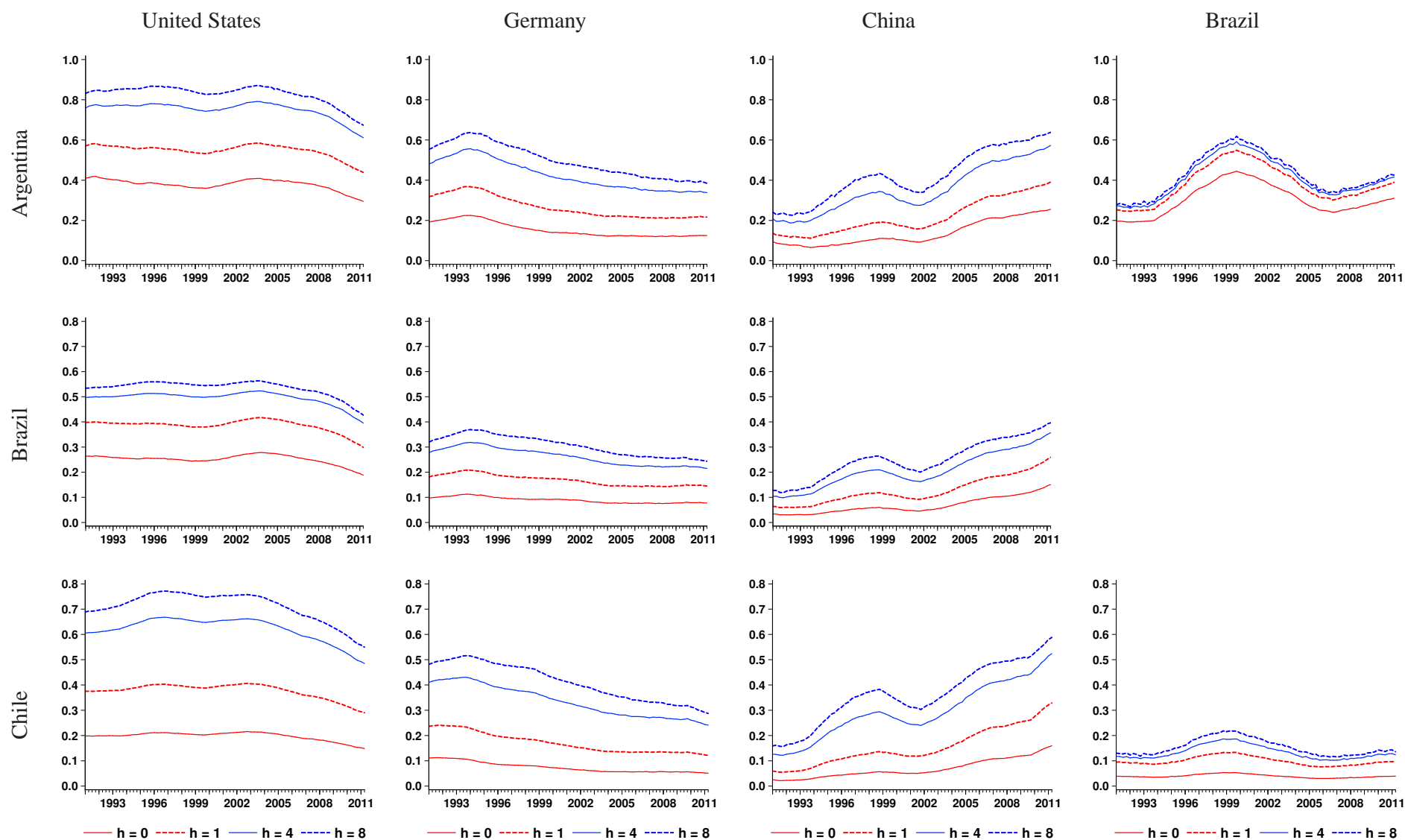
**Notes:** Each graph shows the relative effect of a shock in country *i* (column) on country *j* (rows), letting the trade matrix $W_t$ vary through time, and for various values of *h*. See equation (11). The scale of the vertical axis may vary across rows.

**Figure 2 (cont'd).** *Time profile of relative effects of foreign shocks in Latin America: 1991 to 2011*

**Notes:** Each graph shows the relative effect of a shock in country $i$ (column) on country $j$ (rows), letting the trade matrix $\mathbf{W}_t$ vary through time, and for various values of $h$. See equation (11). The scale of the vertical axis may vary across rows.
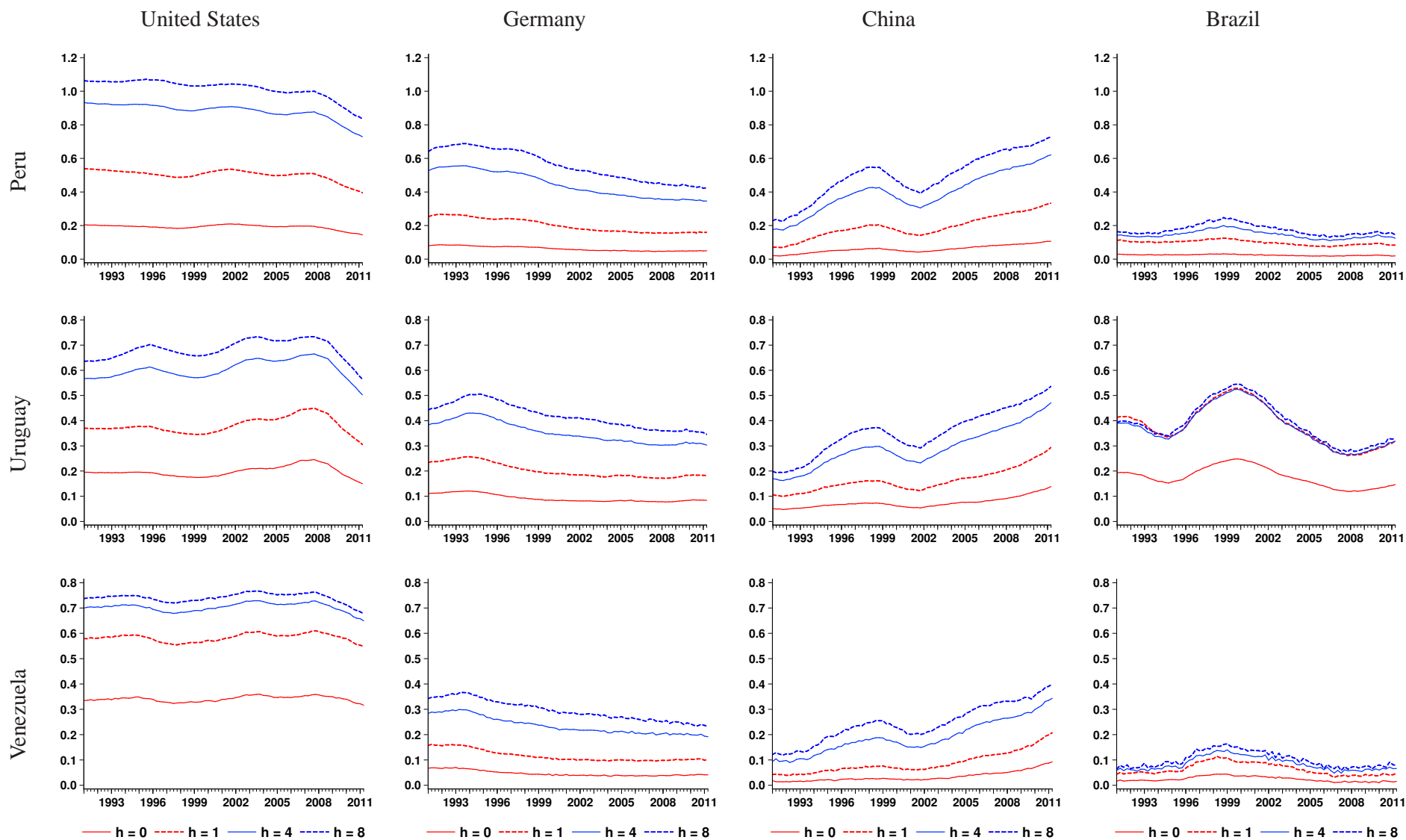
**Notes:** Each graph shows the relative effect of a shock in country $i$ (column) on country $j$ (rows), letting the trade matrix $W_t$ vary through time, and for various values of $h$. See equation (11). The scale of the vertical axis may vary across rows.

**Table 3.** *Counterfactual simulations for the period 2006 - 2011 (average annualized growth rates)*

| | Actual | Counterfactual | | | | |
|---|---|---|---|---|---|---|
| | | Export weights 1995 - 2000 $W_1$ | Direct effect $W_3 - W_1$ | Indirect effect $W_2 - W_3$ | Overall effect $W_2 - W_1$ | Export weights 2006 - 2011 $W_2$ |
| Argentina | 7.22 | 4.46 | 0.70 | 2.61 | 3.30 | 7.76 |
| Brazil | 4.31 | 2.61 | 0.53 | 1.68 | 2.21 | 4.82 |
| Chile | 3.55 | 0.79 | 0.92 | 2.47 | 3.39 | 4.18 |
| Colombia | 4.51 | 3.71 | 0.13 | 0.89 | 1.02 | 4.73 |
| Ecuador | 4.06 | 2.66 | 0.06 | 1.66 | 1.72 | 4.38 |
| Mexico | 2.10 | −0.58 | 0.36 | 3.02 | 3.38 | 2.80 |
| Peru | 7.31 | 3.94 | 0.89 | 3.32 | 4.21 | 8.15 |
| Uruguay | 6.48 | 5.10 | 0.15 | 2.08 | 2.22 | 7.32 |
| Venezuela | 4.91 | 3.77 | 0.33 | 1.34 | 1.67 | 5.45 |
| Average | 4.94 | 2.94 | 0.45 | 2.12 | 2.57 | 5.51 |

trade structure in the rest of the world fixed at historical levels. Mechanically, the rows of $W_t$ for non-Latin American countries are set to their 1994 - 2000 averages ($W_1$), whereas those corresponding to Latin American economies are set to there 2006 - 2011 averages ($W_2$).

The direct effect therefore is the difference between the growth rates obtained from the $W_3$ run with respect to the results of the $W_1$ run, which are reported in the third column of Table 3. The fourth column of Table 3 shows the residual effects of this simulation with respect to the $W_2$ run, and these figures can be regarded as the indirect effects of the new trade structure.

The simulations in Table 3 show that, on average, out of the 2.57 percent effect on growth that can be attributed to the differences between trade structures, only a moderate 0.45 percent comes form redirecting trade towards fast-growing economies. Most of the effect, a remarkable 2.12 percent, corresponds to indirect effects that can be thought of the multipliers induced by the Chinese juggernaut during the 2006 - 2011 period.

Some of the findings in Table 3 at a country level are also illustrative on the workings of the SVAR model. Firstly, the strongest (above average) direct effects occurred to countries that are large exporters of commodities for which China has shown a particular appetite in the 2000s: Chilean cooper, Peruvian cooper, zinc, lead and fishmeal, Argentinean soybeans and Brazil iron ore and soybeans. Thus a large effect of impact help explain the above average indirect effects reported for Argentina, Chile and Peru. This effect mirrors the Chinese export share for each country (see Table 1), which may have been inflated by booming commodity prices.

Secondly, the Mexican case illustrates how due to multiplier effects, a shock to a country can have a large impact on others that are relatively minor bilateral trading partners. The results on Mexico are seemingly unusual: the combination of a well-below average direct effect and very strong indirect effects. As it can be seen in Table 1, the United States remains by far the main Mexican trade partner, despite the increase in the Chinese share. The extremely low growth rate of Mexico using trade shares from the 1990s (−0.58 percent) is a direct consequence of the exposition of this economy to the American economy, which experienced a recession after the 2008 crisis. In the new trade structure, the Unites States share is marginally smaller, so a relatively modest direct effect in the Mexican case should not be surprising. The large indirect effect is due to the effects the new trade structure has had on the American economy, which are magnified in Mexico (as revealed in Figures 1 and 2, the medium-term elasticities of a American shock are greater than one). Thus, in our simulations the United States, as well as many other industrialized economies, is implicitly benefiting for the new trade configuration.

# 4 Concluding remarks

In this paper we have developed a SVAR model with rich feedbacks, direct and indirect, for 29 economies worldwide. Aggregation restrictions using trade shares are formally tested and then imposed to achieve both a rather parsimonious system and the identification of a structural form. As the trade shares are time-varying, so are the impulse-response function of the SVAR, which enables us to analyze the changes that the effects on Latin American growth of shocks in the United States, China, Germany and Brazil, have undergone.

Our results point out to relatively stable effects on Latin American growth of shocks in the United States, although they seem to have diminished by the end of our sample. In contrast, the indirect effects of a German shock have reduced steadily during the last decade, somehow displaced by particularly strong indirect effects of a Chinese shock. These findings support the idea that the more prominent presence of China in the world economic scene have had a potentially large impact on third countries, even if they are minor trade partners.

Counterfactual simulations show that a remarkable proportion of the vigorous Latin American growth experienced in the period 2006 - 2011 can be attributed to second-round effects, while only a modest fraction is due to changing trade orientation towards fast-growing emerging economies. These findings have profound policy implications. We reckon that part of the direct effect may be the outcome of well-suited trade policies, i.e. selecting as trade partners (for instance, through the enactment of formal trade agreements) those economies that can sustain the demand for the products for which a country has comparative advantages. Yet, we estimate that these policies would have granted Latin American countries an increase of (at most) 0.5 percent in its growth rate. This is a significant result but may not be enough to move towards a sustainable high growth path.

On the other hand, most Latin American counties remain rather small open economies, simply spectators of the world economic scene. Our results point out that even Brazil, despite its size, is still unavailable of influencing the dynamics of economies beyond the region. As a whole, Latin America still seems vulnerable to external shocks, so that the strong positive indirect effect on growth reported above, can be regarded as sheer "good luck" (a particularly good realization of shocks). It is, therefore, a core policy challenge for each Latin American country to seize on such favorable external conditions, which albeit persistent are likely to be temporary, to promote policies aimed to reduce its vulnerability to foreign shocks.

There are several ways in which China may have affected Latin America: commercial, financial and by sustaining high commodities prices in international markets. Even though some emphasis was given to the commercial channel, we have not truly attempted to make a distinction among these channels and we reckon do it so constitutes an interesting avenue for future research. In particular, to explicitly model and quantify the effects of Chinese demand on the terms of trade of commodity exporters, such as most Latin American countries (see, for instance, Abeysinghe, 2001). Another interesting extension is to assess the effects of global shocks (for instance, by considering the presence of common factors in the structural perturbations), and especially to enquire whether the redirection of trade towards emerging markets has delivered the diversification gains that theory predicts.

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