Does trade integration imply growth in Latin America? Evidence from a dynamic spatial spillover model *

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Abstract

To investigate the role of intra-regional trade integration on economic growth in Latin America, we develop a multilevel spatial production network model with time-varying parameters. The theoretical model is established for a multi-country and multi-sectoral economy. The reduced-form econometric framework relies partly on observation-driven dynamic processes. The finite-sample properties of the maximum likelihood estimates are investigated through a Monte Carlo study. The empirical study is for six countries in Latin America. The findings suggest that intra-country spillovers configure an important factor for explaining growth, while the importance of domestic spillovers is limited. The growth volatility is substantively reduced since 2005.

Key words: Spatial network model, multilevel model, time-varying parameters, economic modeling, trade liberization, growth.

JEL codes: C31, C32, F14, F43

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1 Introduction

This paper introduces an econometric framework for measuring time-varying cross-sectional dependence in multilevel spatial models where variables can interact at different levels of aggregation. In particular, we consider a dynamic spatial model in which the spillover effects of domestic (*within*) and international (*between*) trade linkages can be disentangled. The spatial econometric model is obtained as a reduced form of a structural economic model that is consistent with equilibrium conditions for a multi-country multi-sectoral economy; see the discussion on production networks in Long and Plosser (1983) and Carvalho and Tahbaz-Salehi (2019). Furthermore, we build on the dynamic panel data model with a time-varying parameter as proposed in Blasques et al. (2016), by introducing a set of time-varying parameters which allow for cross-sectional dependence to change dynamically over time. The empirical relevance of the model is shown by measuring the importance of trade integration on growth dynamics in Latin America.

Our research contributes to two strands of literature. First, we contribute to the spatial econometrics literature, where spatial autoregressive models have been used for different purposes, including estimating regional price elasticity (Aquaro et al., 2021; Mueller and Loomis, 2008), assessing the effects of extreme temperatures across regions using a network approach (Winter et al., 2016; Sain et al., 2011), estimating the rate of convergence in the context of spatial Solow and spatial Schumpeterian growth models (Fingleton and López-Bazo, 2006; Ertur and Koch, 2007), and analyzing spatial dependence in financial markets (Wied, 2013; Arnold et al., 2013; Herskovic et al., 2020). In all of these studies, the spatial parameter itself is treated as a static time-invariant parameter. Blasques et al. (2016) have however developed an econometric framework with a time-varying spatial dependence parameter using a score-driven filter introduced in Creal et al. (2013) and Harvey (2013). We extend this framework by considering a set of time-varying dependence parameters which are attributable to different levels of data aggregation.

Second, we contribute to the economics literature concerning production networks and trade where the importance of trade integration for growth in the context of a network of sectoral spillovers is discussed; see e.g. Bernard and Moxnes (2018). Since the early 1990s, government policies have aimed to promote trade integration as a mechanism for boosting growth and reducing growth volatility. Whether trade integration has resulted in positive or negative effects on growth is an outstanding question. In the seminal work of Frankel and Romer (1999) it is argued that trade brings positive effects to growth. Dollar and Kraay (2004) suggest that trade has reduced poverty levels worldwide. Obstfeld and Rogoff (2001) document that trade has limited growth effects due to several market frictions such as trade costs and labor market rigidities. Finally, in Goldberg and Pavcnik (2007) it is suggested that country-specific factors may have exacerbated the negative distributional effects of trade liberalization.

The mechanism of how trade impacts growth is discussed widely in the literature and it is often said to be either due to learning-by-importing or learning-by-exporting (Amiti and Konings, 2007), or to improving firm capabilities (Grossman and Helpman, 1991). The role of domestic factors is also widely stated as a factor of how trade can lead to growth, see, for example, Easterly et al. (1993), Hall and Jones (1999), and Rodrik (1999). Empirical studies on trade and growth have faced some challenging inference issues. For example, the measurement of trade liberalization and its identification by means of instrumental variable regressions, have led to interesting studies, including Frankel and Romer (1999), Sachs and Warner (1999) and Wacziarg and Welch (2008). To the best of our knowledge, there is no econometric methodology that is capable of distinguishing domestic and external growth spillovers within an economic modeling framework. In this paper, we propose an econometric dynamic model that aims to disentangle these domestic and external spillovers effects simultaneously. This formulation accounts for the equilibrium conditions for multi-country multi-sectoral models in a production network. Hence, our reduced form econometric model is consistent with the structural equations of economic trade models.

Our empirical model formulation and analysis differs from earlier contributions. For example, the estimation procedure controls for growth volatility that can be misguidedly attributed to either domestic or external spillovers (Forbes and Rigobon, 2002). Further, we apply our methodology to disentangle the growth spillover effects of intra-regional trade (*between*) from domestic (*within*) linkages in selected Latin American countries: Argentina, Brazil, Chile, Colombia, Mexico and Peru. The results suggest that *between* spillovers configure an important factor for explaining growth dynamics, while the *within* importance has a limited impact. Hence, intensifying domestic linkages has a reduced potential for boosting growth. In addition, our empirical findings suggest that growth volatility has consistently declined over time, especially after the large increase of export growth in 2005.

The remainder of the paper is organized as follows. Section 2 introduces the dynamic spatial model for production networks of multi-country model. In Section 3 the details of the econometric estimation method are discussed. Section 4 presents the results of a Monte Carlo simulation study. Section 5 presents the results of the empirical study on intra-regional trade in Latin America. Section 6 concludes.

2 A dynamic spatial model for production networks

In this section, we consider a structural economic model for production networks of multi-country economies. The structural equations provide a justification from an economic theory perspective of the reduced-form econometric model specification in Section 3. It further provides a theoretical interpretation of the empirical findings reported in Section 5 for Latin America countries. The economic model is an extension of the formulation in Carvalho and Tahbaz-Salehi (2019) for a setting with multiple countries and with sectoral input-output linkages for each country.

Consider an economic trade system for N countries, labeled as country $i = 1, \ldots, N$, and for J sectors, labeled as sector $j = 1, \ldots, J$. Assume that the final good's producers in each sector employ a Cobb-Douglas production technology with constant return to scale to transform intermediate inputs and labor into final products. The output of sector j in country i at time t is given by

$$Y_{i,j,t} = \Phi_{i,j} Z_{i,j,t} H_{i,j,t}^{\alpha_{i,j}} \prod_{k=1}^{J} \left\{ \left(\prod_{v \neq i=1}^{N} M_{v,j,k,t}^{E} \right)^{\left(1-x_{i,j,k}\right)\lambda_{i,v}} \left(M_{i,j,k,t} \right)^{x_{i,j,k}} \right\}^{\varphi_{i,j,k}} \tag{1}$$

where $Z_{i,j,t}$ is a Hicks-neutral productivity shock, $H_{i,j,t}$ is the labor demand of sector j in country i, $M_{i,j,k,t}$ represents the materials demanded by sector j from the sector k in country i, $M_{v,j,k,t}^{E}$ is the materials demanded by sector j in country i from sector k in country v, Φ_{ij} is a normalization constant whose value only depends on model parameters[1], $\alpha_{i,j} > 0$ denotes the share of labor in sector j's production technology, $x_{i,j,k}$ represents the preference for using domestic inputs and $(1 - x_{i,j,k})$ for foreign inputs, $\lambda_{i,v}$ is the trade preferences with country v with $\sum_{v \neq i}^{N} \lambda_{i,v} = 1$, and $\varphi_{i,j,k}$ is the input preference for sector k's products. The assumption of constant returns to scale in each sector implies that $\alpha_{i,j} + \sum_{k=1}^{J} \varphi_{i,j,k} = 1$. Each sector uses both domestic and imported materials from other sectors; this fact represents a source of interconnectedness in our economic network model.

Next, we determine the optimal input allocation. The final producers choose their demand for labor and intermediate inputs in order to maximize profits

$$\pi_{i,j,t} = Y_{i,j,t} - \Psi_{i,t} H_{i,j,t} - \sum_{k=1}^{J} M_{i,j,k,t} - \sum_{v \neq i}^{N} \sum_{k=1}^{J} M_{v,j,k,t}^{E} \tag{2}$$

where $\Psi_{i,t}$ denotes wages[2]. The first order conditions corresponding to firms in sector j are

[1] In what follows, we set the value of this constant to

$$\Phi_{i,j} = \prod_{k=1}^{J} \left\{ \varphi_{i,j,k} x_{i,j,k}^{x_{i,j,k}} (1 - x_{i,j,k})^{(1-x_{i,j,k})} \prod_{v} \lambda_{i,v}^{(1-x_{i,j,k})\lambda_{i,v}} \right\}^{-\varphi_{i,j,k}} \alpha_{i,j}^{-\alpha_{i,j}}.$$

This choice has no bearing on the results.

[2] In addition, the price index is normalized towards one for simplicity.

given by

$$\Psi_{i,t} H_{i,j,t} = \alpha_{i,j} Y_{i,j,t} \ , \quad M_{i,j,k,t} = \varphi_{i,j,k} x_{i,j,k} Y_{i,j,t} \quad \text{and} \quad M^E_{v,j,k,t} = \varphi_{i,j,k} \lambda_{i,v} (1 - x_{i,j,k}) Y_{i,j,t}.$$

In addition, it is assumed that the economy is populated by a representative household who supplies one unit of labor inelastically and has logarithmic preferences over the J goods produced by the J sectors, given by

$$v_i \ (C_{1,t}, \ldots, C_{J,t}) = \sum_{j=1}^{J} \beta_{i,j} \log(C_{i,j,t}/\beta_{i,j}) \tag{3}$$

where $C_{i,j,t}$ is the amount of final good j consumed. The constant $\beta_{i,j}$ measures various goods' shares in the household's utility function, normalized such that $\sum_{j=1}^{J} \beta_{i,j} = 1$. The consumers budget constraint is given by $\sum_{j=1}^{J} C_{i,j,t} \leq \Psi_{i,t}$, where it is assumed that $\Psi_{i,t} = Y_{i,t}$, which implies that wages are the only source of income. Hence, we are omitting capital rents. Therefore, the first order condition implies that $C_{i,j,t} = \beta_{i,j} \Psi_{i,t}$.

2.1 The equilibrium

By plugging the expressions for $H_{i,j,t}$, $M_{i,j,k,t}$ and $M^E_{v,j,k,t}$ into equation (1), the equilibrium value for total output in country i, $Y^*_{i,t}$, is given by[3]

$$\log Y^*_{i,t} = \sum_{j=1}^{J} s^*_{i,j,t} \log Z_{i,j,t} \tag{4}$$

where $s^*_{i,j,t} = Y^*_{i,j,t}/Y^*_{i,t}$ is defined as the Domar weight, which measures the importance of a given sectoral income in the economy. In addition, the market clearing condition that

[3]The model assumptions imply that $\sum_{j=1}^{J} s_{i,j,t} \alpha_{i,j} = 1$.

governs the economy at any point in time is determined by

$$Y_{i,j,t} = C_{i,j,t} + \sum_{k=1}^{J} M_{i,k,j,t} + \sum_{v\neq i=1}^{N} \sum_{k=1}^{J} M^E_{i,k,j,t|v} - \sum_{v\neq i=1}^{N} \sum_{k=1}^{J} M^E_{v,j,k,t} \tag{5}$$

where $M^E_{i,j,k,t|v}$ denotes material exports from country i to country v. Meanwhile, $M_{i,k,j,t}$ is the sector k import from sector j. This reveals the importance of sector j as input supplier in the economy. Therefore, when replacing the first order conditions in equation 5, the equilibrium value for the Domar weight satisfies the following condition

$$\begin{aligned}\left[1 + \sum_{k=1}^{J} \varphi_{i,j,k}(1 - x_{i,j,k})\right] s_{i,j,t} = \beta_{i,j} + \sum_{k=1}^{J} \varphi_{i,k,j} x_{i,k,j} s_{i,k,t} + \\ \sum_{v\neq i=1}^{N} \sum_{k=1}^{J} \varphi_{v,k,j}(1 - x_{v,k,j}) \lambda_{v,i} \frac{(Z_{v,j,t})^{-\alpha_{v,j}}}{(Z_{i,jt})^{-\alpha_{i,j}}} s_{v,k,t}.\end{aligned} \tag{6}$$

In contrast to Carvalho and Tahbaz-Salehi (2019), which determines a constant equilibrium value for the Domar weight, the multi-country setup causes this ratio to be time-dependent due to productivity fluctuations, $(Z_{i,j,t}, Z_{v,j,t})$. Hence, the equilibrium value for the Domar weight can be expressed as

$$s^*_{i,j,t} = \sum_{\tau=1}^{N} \sum_{k=1}^{J} a^{i,j}_{\tau,k,t} \beta_{\tau,k}, \tag{7}$$

where $a^{i,j}_{\tau,k,t}$ is a positive time-varying coefficient that depends on model parameters as well as productivity shocks in country i and v's (see Appendix A for details). Finally, the equilibrium value for the sectoral income can be expressed as

$$Y^*_{i,j,t} = \left(\sum_{\tau=1}^{N} \sum_{k=1}^{J} a^{i,j}_{\tau,k,t} \beta_{\tau,k} \right) \exp \left(\sum_{j=1}^{J} \left(\sum_{\tau=1}^{N} \sum_{k=1}^{J} a^{i,j}_{\tau,k,t} \beta_{\tau,k} \right) \log Z_{i,j,t} \right), \tag{8}$$

where the productivity of trade partner v does not directly affect the equilibrium value of $Y^*_{i,j,t}$, but it does amplify the effects of $Z_{i,j,t}$ through the time-varying coefficient $a^{i,j}_{\tau,k,t}$. This implies growth spillovers.

2.2 Model representation

We now proceed to linearize the market clearing condition given in equation (5), around the equilibrium value,

$$\begin{aligned}\tilde{y}_{i,j,t} =&\beta_{i,j}\frac{\tilde{\Psi}_{i,t}}{s^*_{i,j,t}} + \sum_{k=1}^{J}\varphi_{i,k,j}x_{i,k,j}\frac{Y^*_{i,k,t}}{Y^*_{i,j,t}}\tilde{y}_{i,k,t} \\ &+ \sum_{v\neq i=1}^{N}\sum_{k=1}^{J}\varphi_{v,k,j}(1-x_{v,k,j})\lambda_{v,i}\frac{Y^*_{v,k,t}}{Y^*_{i,j,t}}\tilde{y}_{v,k,t} - \sum_{k=1}^{J}\varphi_{i,j,k}x_{i,j,k}\tilde{y}_{i,j,t}\end{aligned} \tag{9}$$

where the data $\tilde{y}_{i,j,t}$ is given by

$$\tilde{y}_{i,j,t} = \frac{Y_{i,j,t} - Y^*_{i,j,t}}{Y^*_{i,j,t}}$$

and the expressions $\varphi_{i,k,j}x_{i,k,j}$ and $\varphi_{v,k,j}(1-x_{v,k,j})\lambda_{v,i}$ are elements of the input-output matrix with trade linkages. The input-output (IO) matrix summarizes trade relationships within industries and between countries. Therefore, the input-output matrix can be represented by a weighted directed graph on $N \times J$ vertices, with the element $\{\omega_{i,k,j,t}\}$ revealing the importance of sector j as input supplier to sector k, and $\sum_{k=1}^{J}\omega_{i,k,j,t} = 1$. Similarly, $\{\omega^i_{v,k,j,t}\}$ reveals the importance of sector j as input supplier to sector k in country v, with $\sum_{v\neq i=1}^{N}\sum_{k=1}^{J}\omega^i_{v,k,j,t} = 1$. Those linkages are represented as known matrices.

Meanwhile, the equilibrium output ratios can be reformulated such that

$$\rho^w_{i,k,t} = \frac{Y^*_{i,k,t}}{\left(1+\sum_{k=1}^{J}\varphi_{i,j,k}x_{i,j,k}\right)Y^*_{i,j,t}} \tag{10}$$

and,

$$\rho^b_{v,k,t} = \frac{Y^*_{v,k,t}}{\left(1+\sum_{k=1}^{J}\varphi_{i,j,k}x_{i,j,k}\right)Y^*_{i,j,t}} \tag{11}$$

with $\rho^w_{i,k,t}$ and $\rho^b_{v,k,t}$ are time-varying parameters aimed at capturing *within* and *between* spillovers from domestic and international technological gains. We further discuss the role of these time-varying spillover parameters in the following section. In addition we consider identification restrictions and additional structure imposed for the estimation of our empirical model. Finally, the linearized market clearing condition in terms of growth rates can be represented by

$$y_{i,j,t} = b_{i,j,t} + \sum_{k=1}^{J} \rho^{w}_{i,k,t} \omega_{i,k,j,t} y_{i,k,t} + \sum_{v \neq i=1}^{N} \sum_{k=1}^{J} \rho^{b}_{v,k,t} \omega^{i}_{v,k,j,t} y_{v,k,t} + \mu_{i,j,t} \tag{12}$$

where $y_{i,j,t} = \tilde{y}_{i,j,t} - \tilde{y}_{i,j,t-1}$ and

$$\begin{aligned} b_{i,j,t} =& \frac{\beta_{i,j}}{1 + \sum_{k=1}^{J} \varphi_{i,j,k} x_{i,j,k}} \left(\frac{\tilde{\Psi}_{i,t}}{s^{*}_{i,j,t}} - \frac{\tilde{\Psi}_{i,t-1}}{s^{*}_{i,j,t-1}} \right), \\ \mu_{i,j,t} =& \sum_{k=1}^{J} \omega_{i,k,j,t} \tilde{y}_{i,k,t-1} (\rho^{w}_{i,k,t} - \rho^{w}_{i,k,t-1}) + \sum_{v \neq i=1}^{N} \sum_{k=1}^{J} \omega^{i}_{v,k,j,t} \tilde{y}_{v,k,t} (\rho^{b}_{v,k,t} - \rho^{b}_{v,k,t-1}) \end{aligned}$$

with $(\rho^{w}_{i,k,t} - \rho^{w}_{i,k,t-1})$ and $(\rho^{b}_{v,k,t} - \rho^{b}_{v,k,t-1})$ the disturbance terms. The dynamics of the spillovers parameters is further described in section 3. Meanwhile, $b_{i,j,t}$ measures the aggregate effect of output growth, broadly captured by the intercept in linear regressions. In what follows, we assume constant intercept. Notice that spillovers variables are not properly accounted for in growth decomposition analysis.

2.3 Time-varying spatial dependence

In this section, we discuss the role of the time-varying spillover parameters $\rho^{w}_{i,k,t}$ and $\rho^{b}_{v,k,t}$ for growth. The *within* sector spillover, $\rho^{w}_{i,k,t}$, captures the relative importance of sector k with respect to the input provider j in country i's total output. Because the Domar weight depends on a series of productivity shocks captured by the time-varying coefficient $a^{i,j}_{\tau,k,t}$, an increase of this ratio reflects productivity improvements in the sectors (in country i as well in trade partners v's) for which k is an input provider, resulting in higher demand for k's inputs. Sector j is an input provider of sector k, therefore, there is an indirect effect to j.

Similarly, the *between* spillover, $\rho^b_{v,k,t}$, reflects the relative importance of sector k in country v's total output with respect to the importance of sector j in country i's total output. Therefore, an increase on the productivity level in sectors for which the sector k in country v is an input provider, would increase the demand for k's inputs. In addition, the *between* spillover captures the direct effect of sectoral productivity shocks $Z_{v,j,t}$ in the trade partner country v. An increase on the sectoral productivity level of country v relative to country i, would result in positive knowledge spillovers in sector j, in a way of learning-by-exporting.

These mechanisms configure the trade spillovers to growth, typically summarized in either learning-by-importing or exporting (Amiti and Konings, 2007) or improving firm capabilities (Grossman and Helpman, 1991; Pavcnik, 2002). Notice that trade spillovers play the role of growth amplifiers whenever there is a productivity improvement on trade partners.

In the remainder of this paper, we will impose a further spatial structure on these parameters, which will allow us to turn this structural economic model into an empirical dynamic spatial model with identifiable parameters that can be estimated from the data. In particular, we assume that these parameters follow a common factor-structure across countries and sectors,

$$\rho^w_{i,k,t} = \rho^w_t + v^w_{i,k,t} \quad \text{and} \quad \rho^b_{v,k,t} = \rho^b_t + v^b_{v,k,t} \tag{13}$$

where ρ^w_t and ρ^w_t are the common (or fully pooled) time-varying *between* and *within* spillover coefficients, respectively, and where $v^w_{i,k,t}$ and $v^b_{v,k,t}$ are mean zero processes which are also conditional on all past data $\mathcal{F}_{t-1}$, i.e. $\mathbb{E}(v^w_{i,k,t}|\mathcal{F}_{t-1}) = 0$ and $\mathbb{E}(v^b_{v,k,t}|\mathcal{F}_{t-1}) = 0$. This model effectively allows for country-specific and sector-specific spillover parameters $\rho^w_{i,k,t}$ and $\rho^b_{v,k,t}$, while at the same time ensuring that the conditional expectation of the spillover parameters are country and sector invariant, i.e.

$$\mathbb{E}(\rho^{w}_{i,k,t}|\mathcal{F}_{t-1}) = \mathbb{E}(\rho^{w}_{t}|\mathcal{F}_{t-1}) \quad \text{and} \quad \mathbb{E}(\rho^{b}_{v,k,t}|\mathcal{F}_{t-1}) = \mathbb{E}(\rho^{b}_{t}|\mathcal{F}_{t-1}).$$

In the empirical study, we will show that our model, even with these restrictions, is capable of capturing both the cross-sectional variation and temporal dynamics of the data well.

The factor model structure for the spillover parameters introduces dynamic conditional volatility in the error term. This feature is implied by the country-specific and sector-specific spillover variations $v^{w}_{i,k,t}$ and $v^{b}_{v,k,t}$ which are placed in the error term of our empirical model in a way of $\sum_{k=1}^{J} v^{w}_{i,k,t}\omega_{i,k,j,t}y_{i,k,t}$ and $\sum_{v\neq i=1}^{N}\sum_{k=1}^{J} v^{b}_{v,k,t}\omega^{i}_{v,k,j,t}y_{v,k,t}$, respectively. Hence, both terms are subject to temporal dynamics. The dynamic conditional volatility property then follows from the expressions in (13) and by substituting $\rho^{w}_{i,k,t}$ and $\rho^{b}_{v,k,t}$ in (12).

3 A reduced-form dynamic spatial econometric model

In this section, we introduce a reduced-form spatial econometric model that describes the structural growth rate model in equation (12). The spatial econometric model is based on a multilevel score-driven specification that accommodates time-varying spatial spillovers, not only within countries, but also between sectors, and between countries. The model extends existing score-driven spatial models, as in Blasques et al. (2016) and Catania and Billé (2017), by introducing a multilevel dynamic spatial spillover structure. Consider the following vector-valued model formulation

$$y_t = b\mathbf{1} + \rho^{w}_{t}W^{w}_{t}y_t + \rho^{b}_{t}W^{b}_{t}y_t + Z_t\phi + \epsilon_t, \qquad \epsilon_t \sim p_{\epsilon}(\epsilon|\Sigma_t), \tag{14}$$

where $y_t = (y'_{1,t}, \dots, y'_{N,t})'$ is an $(N \cdot J)$-dimensional vector of multilevel cross-sectional observed trade (or trade growth) at time t. Here $y_{i,t} = (y_{i,1,t}, \dots, y_{i,J,t})'$, where $y_{i,j,t}$ is the trade for country $i = 1, \dots, N$, sector $j = 1, \dots, J$, at time $t = 1, \dots, T$, and ϵ_t is the

$(N \cdot J)$-dimensional vector of error terms with probability density function p_ϵ that has mean zero and a time-varying covariance matrix Σ_t. Furthermore, we have that Z_t is a matrix of exogenous regressors, with ϕ denoting the associated parameter vector of coefficients. ρ_t^w and ρ_t^w are the common time-varying *between* and *within* spillover coefficients from equation (13), and W_t^w and W_t^b are block weighting matrices that capture domestic and international trade interactions. More specifically, W_t^w and W_t^b take the following forms

$$W_t^w = \begin{pmatrix} W_{1,1,t}^w & 0 & \dots & 0 \\ 0 & W_{2,2,t}^w & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & W_{N,N,t}^w \end{pmatrix}, \qquad W_t^b = \begin{pmatrix} 0 & W_{1,2,t}^b & \dots & W_{1,N,t}^b \\ W_{2,1,t}^b & 0 & \dots & W_{2,N,t}^b \\ \vdots & \vdots & \ddots & \vdots \\ W_{N,1,t}^b & W_{N,2,t}^b & \dots & 0 \end{pmatrix},$$

where $W_{i,k,t}^b$, for $i, k = 1, \dots, N$, is a $J \times J$ known weighting matrix that is constructed from the input-output (IO) matrices.

The model given in equation (14) entails that each entry $y_{i,j,t}$ of the vector $y_{i,t}$ depends on the other entries $y_{v,j,t}$ for $v \neq i = 1, \dots, N$ and $j = 1, \dots, J$. It can be shown that the model can capture nonlinear feedback effects across units by rewriting it as

$$y_t = X_t\gamma + W_t\rho_t X_t\gamma + (W_t\rho_t)^2 X_t\gamma + \dots + \epsilon_t + W_t\rho_t\epsilon_t + (W_t\rho_t)^2\epsilon_t + \dots \qquad (15)$$

where $X_t = (\mathbf{1}, Z_t)$, $\gamma = (b, \phi')'$, $\rho_t = (\rho_t^w I_{NJ}, \rho_t^b I_{NJ})'$, and $W_t = (W_t^w, W_t^b)$, which implies that $W_t\rho_t = \rho_t^w W_t^w + \rho_t^b W_t^b$. Equation (15) reveals that $\epsilon_{i,j,t}$ and $X_{i,j,t}\gamma$ for unit (i, j) spills over to other units (v, j). The extent to which the *between* spillovers depend on the magnitude of the link $(v, j) - (i, j)$, which is captured in the matrix W_t^b. On the other hand, the magnitude of the *within* spillovers, $(i, k) - (i, j)$ for all $k \neq j = 1, \dots, J$, are captured by the matrix W_t^w.

In order to ensure that the matrix $I_{NJ} - W_t\rho_t$ is invertible, we impose that the weighting matrices W_t^w and W_t^b are row normalized such that the sum of the entries of each row is equal to 1/2. In this way, the sum of the weighting matrices $W_t^w + W_t^b$ is a row normalized matrix with row entries summing to 1. Furthermore, we restrict ρ_t^w to take values in the interval $(-2c, 2c)$ and ρ_t^b to take values in the interval $(-2+2c, 2-2c)$, where $c \in [0,1]$. Under these restrictions, the sum of the elements in each row of $\rho_t^w W_t^w + \rho_t^b W_t^b$ is in the range between -1 and 1. This ensures the invertibility of the matrix $I_{NJ} - W_t \rho_t$, see Kelejian and Prucha (2010). We note that the standard spatial model without multilevel spillovers is a special case of this formulation when $\rho_t^b = \rho_t^w$ and $c = 1/2$.

As in Blasques et al. (2016), we consider a specification of the dynamic parameters of the model ρ_t^w, ρ_t^b and Σ_t based on the observation-driven or score-driven framework of Creal et al. (2013) and Harvey (2013). For the time-varying spatial dependence parameters ρ_t^w and ρ_t^b, a monotone increasing link function $h : \mathbb{R} \mapsto (-1, 1)$ is considered to ensure that ρ_t^w takes values in $(-2c, 2c)$ and ρ_t^b takes values in $(-2+2c, 2-2c)$ for some $c \in [0,1]$. In particular, we consider the following specification

$$\rho_t^w = 2c \times h(f_t^w), \qquad \rho_t^b = 2(1-c) \times h(f_t^b),$$

where f_t^w and f_t^b are time-varying parameters that take values on the real line and $c \in [0,1]$ is treated as a parameter to be estimated. The time-varying parameters f_t^w and f_t^b are specified as autoregressive processes driven by so-called *score innovations*, we have

$$f_{t+1}^\kappa = \omega^\kappa + A^\kappa f_t^\kappa + B^\kappa s_t^\kappa, \qquad \kappa = w, b, \tag{16}$$

with ω^κ, B^κ and A^κ being fixed (static) unknown parameters, for $\kappa = w, b$, and with the score innovations s_t^κ being defined as the score function (first derivative) of the predictive log-density for y_t, that is

$$s_t^\kappa = \dot{h}(f_t^\kappa) \frac{\partial \rho_t^\kappa}{\partial h} \frac{\partial \ell_t}{\partial \rho_t^\kappa}, \qquad \ell_t = \log p_\epsilon(\epsilon_t | \Sigma_t) + \log |I_{NJ} - W_t \rho_t y_t|, \tag{17}$$

for $\kappa = w, b$, where $\dot{h}(x) = \partial h(x)/\partial x$ and $\epsilon_t = y_t - X_t\gamma - W_t\rho_t y_t$ are in accordance with the model equation in (14). This score-driven model specification entails a unit scaling factor for the score as also considered in Blasques et al. (2016). In a similar way, we specify the time-varying variance Σ_t. We consider $\Sigma_t = \sigma_t^2 I_{NJ}$ with $\sigma_t^2 = \exp(f_t^\sigma)$ where f_t^σ represents the common log-variance of the error vector ϵ_t. The scalar time-varying parameter f_t^σ is specified as an autoregressive process that is also driven by score innovations, we have

$$f_{t+1}^\sigma = \omega^\sigma + A^\sigma f_t^\sigma + B^\sigma s_t^\sigma, \qquad s_t^\sigma = \sigma_t^2 \frac{\partial \ell_t}{\partial \sigma_t^2}, \tag{18}$$

where ℓ_t is defined in (17) and ω^σ, B^σ and A^σ are static parameters which are to be estimated together with the other static parameters in the model.

The specification of the model depends on the choice of the probability density function of the error, p_ϵ. We consider two formulations of the model. The first model is based on the multivariate normal distribution. The second model is based on the multivariate Student's t-distribution. For a multivariate normal ϵ_t, the predictive log-density of y_t is given by

$$\ell_t = \log |I_{NJ} - W_t\rho_t y_t| - \frac{JN}{2}\log(2\pi\sigma_t^2) - \frac{\epsilon_t'\epsilon_t}{2\sigma_t^2},$$

and the score innovations are

$$\begin{aligned} s_t^\kappa &= \dot{h}(f_t^\kappa)\left[\frac{(y_t W_t^\kappa)'\epsilon_t}{\sigma_t^2} - \operatorname{tr}\left((I_{NJ} - W_t\rho_t y_t)^{-1} W_t^\kappa\right)\right], \quad \kappa = w, b, \\ s_t^\sigma &= \frac{\epsilon_t'\epsilon_t}{2\sigma_t^2} - \frac{JN}{2}, \end{aligned} \tag{19}$$

where $\operatorname{tr}(\cdot)$ is the trace operator. On the other hand, when we consider the case that the error terms are from a multivariate Student's t distribution with degrees of freedom parameter λ, the predictive log-density of y_t is

$$\ell_t = \log |Z(f_t^w, f_t^b)^{-1}| + \log \left(\frac{\Gamma(\frac{\lambda+JN}{2})}{|\sigma_t^2 I_{JN}|^{1/2} (\lambda\pi)^{N/2} \Gamma(\frac{\lambda}{2})} \right) - \frac{\lambda + JN}{2} \log \left(1 + \frac{\epsilon_t' \epsilon_t}{\sigma_t^2 \lambda} \right)$$

while the score innovations are given by

$$\begin{aligned} s_t^\kappa &= \dot{h}(f_t^\kappa) \left[\frac{(\lambda + JN)(y_t W_t^\kappa)' \epsilon_t}{\lambda \sigma_t^2 + \epsilon_t' \epsilon_t} - \text{tr} \left((I_{NJ} - W_t \rho_t y_t)^{-1} W_t^\kappa \right) \right], \quad \kappa = w, b, \\ s_t^\sigma &= \frac{(\lambda + JN) \epsilon_t' \epsilon_t}{2(\lambda \sigma_t^2 + \epsilon_t' \epsilon_t)} - \frac{JN}{2}. \end{aligned} \tag{20}$$

A key advantage of the Student's t version of the model is that the score innovations are, to some extent, robust against outliers. Therefore, it controls for extreme observations in the residuals that may otherwise be misguidedly attributed to a sudden change of the spatial correlation parameters ρ_t^w and ρ_t^b. The Student's t model can also approximate arbitrarily well the model with normal errors as $\lambda \to \infty$ entails that the t-score innovations collapse to those obtained from the normal distribution case.

The parameters of the model can be estimated by the method of Maximum Likelihood (ML) as the likelihood function is available in closed form. The parameter vector of the model is $\theta = (\omega^w, \omega^b, \omega^\sigma A^w, A^b, A^\sigma, B^w, B^b, B^\sigma, b, \phi, c)'$ for the normal case and it includes also the parameter λ for the Student's t case. The ML estimator is defined as the parameter vector that maximizes the likelihood function L_T, given by

$$L_T(\theta) = \sum_{t=1}^{T} \ell_t(\theta),$$

where $\ell_t(\theta)$ denotes the predictive log-density expressed as a function of the parameter vector θ. Numerical optimization is used to obtain the ML estimate in practice. The ML estimator of the dynamic score-driven spatial model follows standard asymptotic properties as formally discussed in Blasques et al. (2016).

4 Monte Carlo study

We carry out a Monte Carlo simulation study in order to evaluate the small sample properties of the ML estimator of the parameter vector in the dynamic spatial models with normal errors and Student's t errors. For simplicity, we consider a specification of the spatial multilevel model without exogenous variables and with constant error variance. The sample sizes of N and T are chosen in accordance with the sizes of the dataset which is used in the empirical study of Section 5. The model for data generation process is given by

$$y_t = b\mathbf{1} + \rho_t^w W_t^w y_t + \rho_t^b W_t^b y_t + \epsilon_t, \qquad \epsilon_t \sim p_\epsilon(\epsilon|\sigma^2 I_{JN}), \tag{21}$$

where the spatial dependence parameters are given as in (16) with the constraint $A^w = A^b = A$ and the link function of the spillover parameters h is selected to be the hyperbolic tangent, that is $h() = \tanh()$. The spatial weight matrices, W_t^w and W_t^b, are row-normalized as discussed in Section 2 and they are randomly generated and subsequently are taken as fixed and known. The weighting parameter c is estimated together with the other static parameters. We consider both Gaussian (normal) and Student's t distribution for the error term. The following combinations for the sample size are considered: $(N, T) = (50, 50), (50, 150), (150, 50)$ and $(150, 150)$. The results of the study are based on 500 Monte Carlo replications.

Table 1 reports a summary of the estimation results. We clearly find that almost all parameter estimates are unbiased irrespective of the sample size. This becomes apparent from the fact that the averages of the estimated parameters are close to the corresponding true parameter values. The parameters of the dynamic component of the model, especially B^w and B^b, show some small-sample biases which, however, tend to disappear when the sample size increases, both for N and T. Furthermore, the standard deviations of the parameter estimates decrease when the sample size increases. These findings of decreasing biases and standard deviations indicate that the parameter estimates are consistent.

Table 1: Mean and standard deviation (in parenthesis) of the estimated parameters.

(N,T)		$(50,50)$	$(50,150)$	$(150,50)$	$(150,150)$
θ	True		Gaussian		
b	0.05	0.0510 (0.0057)	0.0505 (0.0028)	0.0513 (0.0046)	0.0501 (0.0022)
B^w	0.03	0.0414 (0.1762)	0.0382 (0.0378)	0.0343 (0.0247)	0.0294 (0.0053)
B^b	0.02	0.0143 (0.1068)	0.0218 (0.0203)	0.0214 (0.0309)	0.0206 (0.0041)
A	0.9	0.8637 (0.1106)	0.8735 (0.0604)	0.8702 (0.0797)	0.8993 (0.0234)
σ^2	0.01	0.0100 (0.0003)	0.0100 (0.0002)	0.0100 (0.0002)	0.0100 (0.0001)
c	0.5	0.4965 (0.0853)	0.4943 (0.0701)	0.4945 (0.0619)	0.5014 (0.0174)
$\bar{\rho}^w = \tanh(\frac{\omega^w}{1-A})$	0.5	0.4901 (0.1141)	0.5063 (0.0961)	0.4871 (0.0905)	0.4984 (0.0323)
$\bar{\rho}^b = \tanh(\frac{\omega^b}{1-A})$	0.2	0.1827 (0.1341)	0.1977 (0.0837)	0.1795 (0.1020)	0.1981 (0.0166)
θ	True		Student's t		
b	0.05	0.0490 (0.0064)	0.0502 (0.0033)	0.0523 (0.0047)	0.0508 (0.0023)
B^w	0.03	0.1027 (0.1869)	0.0790 (0.0821)	0.0629 (0.0405)	0.0506 (0.0115)
B^b	0.02	0.0228 (0.1430)	0.0242 (0.0358)	0.0316 (0.0551)	0.0207 (0.0042)
A	0.9	0.9081 (0.0983)	0.8837 (0.0615)	0.8698 (0.0697)	0.8885 (0.0301)
σ^2	0.01	0.0099 (0.0010)	0.0100 (0.0005)	0.0100 (0.0007)	0.0100 (0.0004)
c	0.5	0.5097 (0.1452)	0.5077 (0.1194)	0.5111 (0.1004)	0.5017 (0.0342)
$\bar{\rho}^w = \tanh(\frac{\omega^w}{1-A})$	0.5	0.4789 (0.1110)	0.5081 (0.1177)	0.4797 (0.1381)	0.4879 (0.0893)
$\bar{\rho}^b = \tanh(\frac{\omega^b}{1-A})$	0.2	0.2180 (0.1473)	0.2110 (0.1119)	0.1690 (0.1575)	0.1915 (0.0835)
λ	8	6.0817 (3.0288)	8.0147 (1.2126)	8.0220 (0.8076)	8.0551 (0.6525)

Figure 1 reports kernel densities of the parameter estimates for the Student's t version of the model. We learn from these kernel densities that the estimated parameters converge to the true parameter values while the shapes of the densities appear to approach the normal distribution, when the sample sizes increases. Overall, these results further confirm the reliability of the ML estimator of the parameter vector θ in relatively small samples, which are approximately equal to the sample sizes considered in the empirical study of the next section.

5 Dynamic spatial spillovers in Latin America trade

To assess in detail whether trade integration imply growth in Latin America (LA), we carry out an empirical study. The economic history of the LA countries is repleted with an assortment of economic crises. To mitigate those impacts, it is suggested that policies

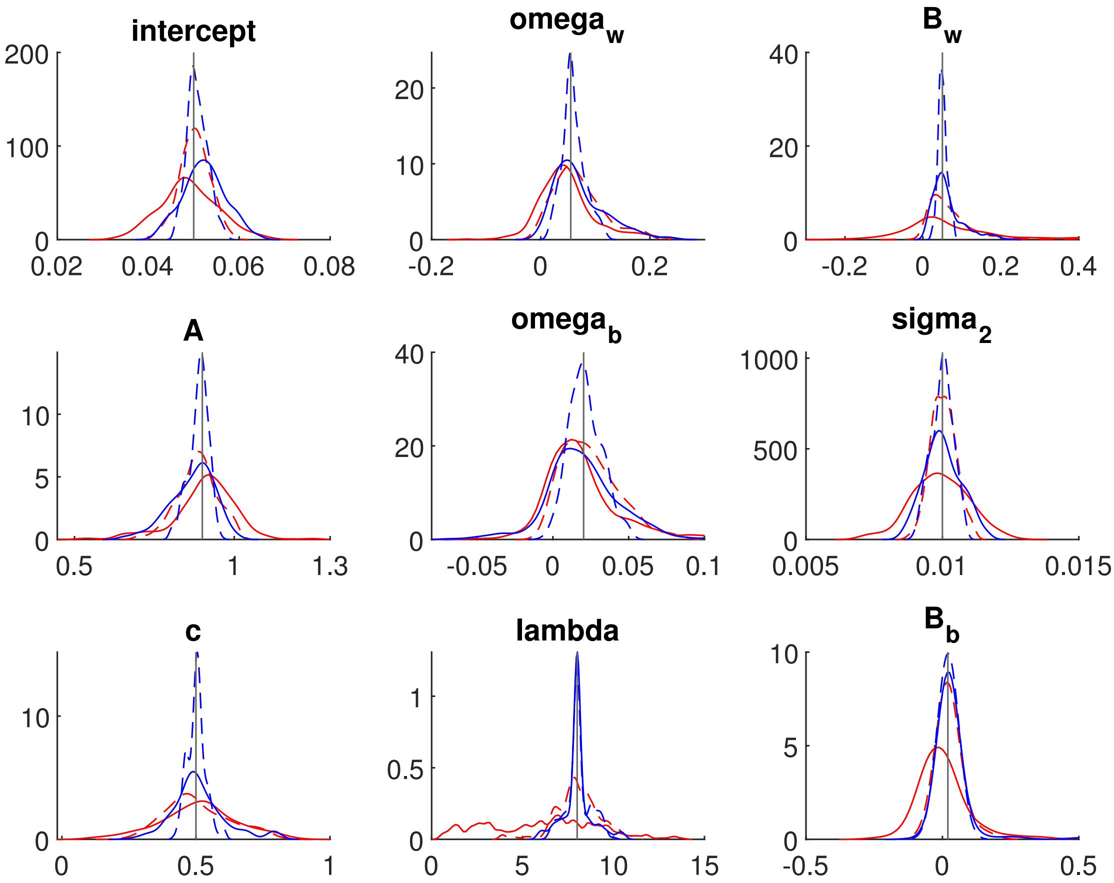

Figure 1: Kernel density estimates for Student's t model parameters. Vertical lines indicates the true parameter values. Red lines corresponds to $N = 50$ and blue lines to $N = 150$. Dashed lines corresponds to $T = 150$ and continuous lines to $T = 50$.

promoting trade openness would allow for "risk-sharing", leading to a reduction on growth volatility. However, empirical studies are rarely able to confirm this policy effect by the data. Obstfeld and Rogoff (2001) document the failure of risk-sharing due to several market frictions such as trade costs. In this empirical study, we adopt our dynamic spatial econometric model which allows us to disentangle the different dynamic effects of domestic and international trade spillovers for growth. Hence, we can identify the types of trade integration that impact the growth more strongly.

The number of intra-regional trade agreements in the LA region has increased since the 1990s. Major trade arrangements include CAFTA-DR, the Southern Common Market (Mercosur) in South America, the Andean Community (CAN), the Caribbean Community and Common Market (CARICOM), the Central American Common Market (CACM), and the Latin American Integration Association (ALADI). As a result, the Latin America's intra-regional exports, as percentage of total exports, averaged 18 percent between 1990 and 2018, which is only below the Euro Area when compared to other regions in the world[4]. Whether this trade integration has resulted in positive or negative spillovers is an ongoing research question, which requires researchers to unmask the role of domestic versus international spillovers. The importance of domestic factors for growth in open economies has been widely studied in the literature; see, for example, Easterly et al. (1993), Hall and Jones (1999), and Rodrik (1999). These authors argue that domestic factors have amplified external shocks in small open economies. In order to understand the shocks mechanism of transmission affecting an economy, it is required to zoom into the sectoral (and even micro) dynamics. Acemoglu et al. (2016) argue that sectoral network-based propagation is larger than the direct effects of the shocks, whereby demand-side shocks propagate upstream (to input-supplying sectors) and supply-side shocks propagate downstream (to customer sectors).

5.1 Data description

The empirical study is based on a country panel of quarterly time series that cover the period from the 1st quarter of 1990 to the 4th quarter of 2019 (1990.Q1 – 2019.Q4, $T = 120$). We investigate the evolution of the time-varying dependence parameters over the sample, aimed at determining the importance of domestic (*within*) and external (*between*) sectoral trade linkages for growth. Solely due to limitations in data availability, our study is narrowed to six countries ($N = 6$): Argentina, Brazil, Chile, Colombia, Mexico and Peru. Nevertheless,

[4]Intra-regional trade between 1990 and 2018 averaged 12 percent within African countries, 13 percent within emerging and developing Asian countries and 50 percent in the Euro Area. Information gathered from the Direction of Trade Statistics (DOTS), International Monetary Fund (IMF).

these economies account for roughly 80 percent of the total Latin America GDP[5].

Sectoral growth

We have constructed a novel value-added data set of nine economic sectors: (1) Agriculture; (2) Mining & quarrying; (3) Manufacturing; (4) Public utilities; (5) Construction; (6) Wholesale, hotels & restaurants; (7) Transports & telecommunication; (8) Finance & real state, and (9) Community & government services. The value-added information is collected from the Economic Commission for Latin America (CEPAL) and from the Statistical Offices of all six LA countries.

Table 2 presents the descriptive statistics of the sectoral growth grouped into countries and sectors. Peru has the highest average sectoral growth in the sample, while Mexico has the lowest growth. The Argentinean sectoral growth ranks as the most volatile given that it has the highest standard deviation. The Mexican growth is the least volatile. Transport & telecommunication has the highest average growth for all six LA countries, while its Manufacturing sector has the lowest growth. Furthermore, the overall growth in Construction is the most volatile, while the sector of Community & government services has the lowest standard deviation. To preserve the significant heterogeneity in variance across sectors, and in accordance with our definition of deviation to equilibrium values, we have standardized the observations separately for each sector and each country (hence, the sample mean is zero and the sample variance is unity, for each sector and each country). In Figure 2 we present the overall average sectoral growth rate for the six LA countries. This time series highlights that growth rates have large swings between bottoms and peaks. Also, the growth in LA appears to get amplified after a crisis.

[5]World Development Indicators (WDI) of the World Bank.

Table 2: Data summary for the sectoral growth rates 1991.Q1-2019.Q4, group average

Country	Mean	St.Dev.	Min.	Max.
Argentina	0.0320	0.0075	-0.1968	0.2680
Brazil	0.0263	0.0034	-0.1426	0.1733
Chile	0.0462	0.0041	-0.1348	0.2265
Colombia	0.0338	0.0035	-0.1256	0.1802
Mexico	0.0250	0.0024	-0.1256	0.1500
Peru	0.0501	0.0044	-0.1398	0.2523
Sector	**Mean**	**St.Dev.**	**Min.**	**Max.**
Agriculture	0.0310	0.0051	-0.1622	0.2924
Mining and quarrying	0.0260	0.0043	-0.1276	0.2298
Manufacturing	0.0252	0.0037	-0.1589	0.1920
Public utilities	0.0405	0.0039	-0.1361	0.2206
Construction	0.0378	0.0120	-0.3319	0.3436
Wholesale, hotels and restaurants	0.0386	0.0041	-0.1768	0.1835
Transport and communication	0.0510	0.0024	-0.0817	0.1733
Finance and real state	0.0408	0.0016	-0.0777	0.1418
Community and government services	0.0291	0.0006	-0.0605	0.0984

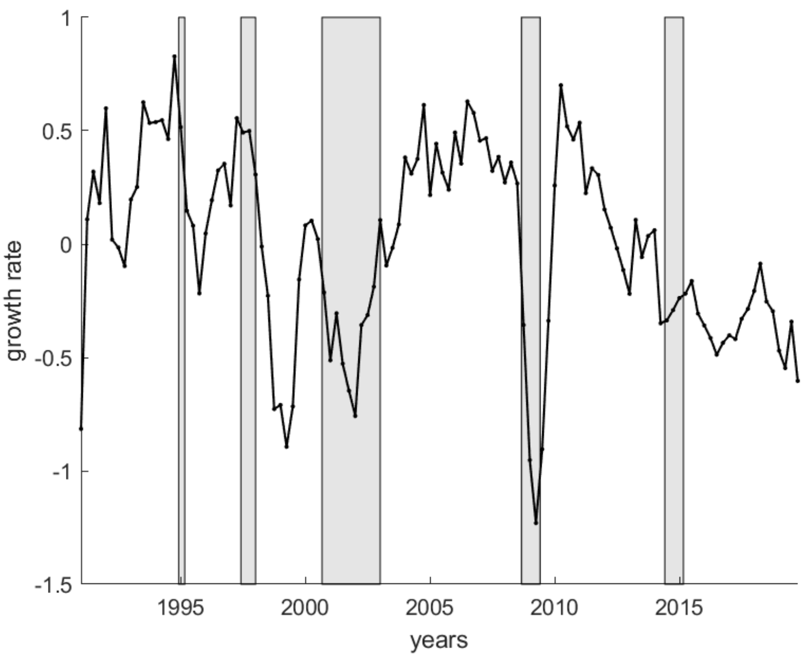

Figure 2: Average sectoral growth rate in Latin American countries. The five shaded areas correspond to (from left to right): *i*) Mexican tequila crisis; *ii*) Asian financial crisis; *iii*) Social and political turmoils; *iv*) US financial Crisis; and *v*) Commodity price shock.

Spatial weights matrix

The input-output (IO) tables are gathered from the Eora global supply chain database[6]. Each IO table includes 25 sectors and it is published on an annual basis from 1990 until 2016. The number of sectors are aggregated to 9 sectors in such a way that the IO matrix matches the sectoral growth database.

5.2 Empirical results

Table 3 presents the estimation results for our proposed spatial econometric model. We consider the model with both static spillovers and time-varying score-driven spillovers, and also with Gaussian and Student's t distributions for the error term. In all four variations of our econometric model, we include a time-varying variance for the error term as specified in equation (18). Therefore, the static models differ from the dynamic models only because of the presence of time-varying spatial spillover parameters. When considering the static model, the estimation results indicate strong empirical evidence of spatial dependence. This finding is especially apparent from the small standard errors and high values of the estimated spillover parameters ρ^w and ρ^b. In addition, given the differences in the reported values of the Akaike Information Criterion (AICc), there is strong evidence that the Student's t model fits the data better than the Gaussian model. When focusing on the dynamic specifications of our model, the results suggest that the dynamic spatial score-driven models significantly outperform their static counterparts, regardless of the distributional assumption. This finding can be elicited from the lower values of the AICc for the dynamic models. The data therefore indicates the presence of time-variation in the spillover parameters ρ_t^w and ρ_t^b. Finally, the regression estimates for real oil prices and real effective exchange rates (REER) are positive and significant, indicating that REER correlates positively with growth.

[6]The EORA database has been used for several international organizations such as the World Bank (the World Development Report, 2020), the International Monetary Fund (World Economic Outlook, 2016; Regional Economic Outlook: Sub-Saharan Africa, 2015), the United Nations (World Investment Report, 2018), among others.

Figure 3 presents the time-varying *within* and *between* spillover parameter estimates for the Gaussian and Student's t models. We observe that the estimated within spillover varies in the range from 0.75 to 1. In contrast, the estimated between spillover fluctuates in the range from -0.2 to 0.5. Furthermore, the estimated between spillover appears to follow a cyclical pattern and declines after crisis periods, while the estimated within spillover seems to show a slightly decreasing pattern. When comparing the results for the Gaussian and Student's t models, we observe that there are no major differences in their time-varying paths of the spatial dependence parameters. The Student's t model shows slightly more smoother changes in the level compared to the one for the Gaussian model. We do expect this finding because the Student's t distribution penalizes outliers in the data more heavily, leading to a time-varying parameter that is more robust. This feature is well documented in the literature; see, for example, Harvey (2013) and Creal et al. (2013). A discussion on the economic interpretation of our results for the within and between time-varying spillovers is presented in Section 5.3 below.

Figure 3: Panel (a) displays the time-varying within spillover parameter for Student's t (black solid line) and Gaussian (red dashed line) distributions. Panel (b) displays the time-varying between spillover parameter. The five shaded areas are as in Figure 2.

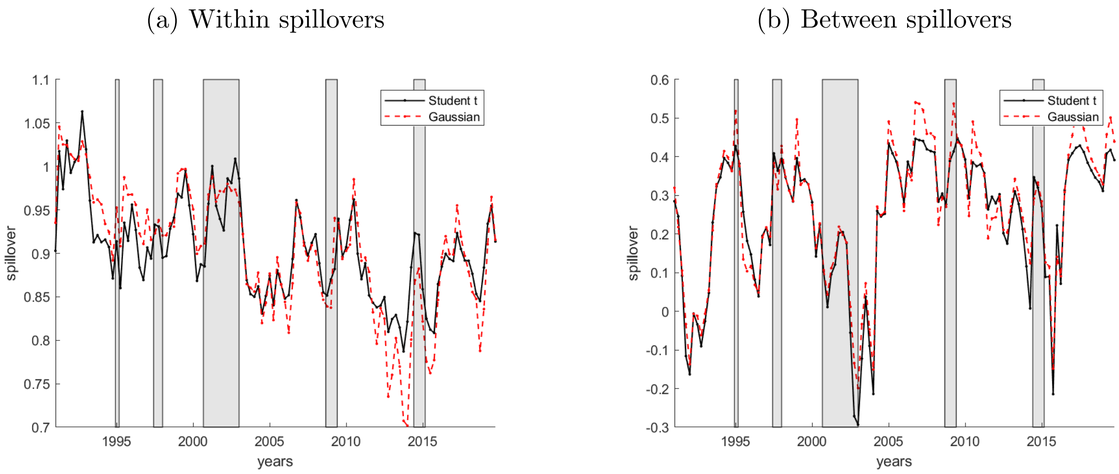

Table 3: Parameter estimates for the static and time-varying spatial models with Gaussian and Student's t distributions. Robust standard errors (sandwich form) are displayed in parenthesis. The last two rows report the values for maximized log-likelihood (logLik) and corrected Akaike Information Criterion (AICc), with finite sample correction to the penalty term.

	Static Model		Time-varying model	
	N	t_λ	N	t_λ
constant	0.0067	0.0069	-0.0003	-0.0026
	(0.0090)	(0.0088)	(0.0111)	(0.0108)
ρ^w	0.9327	0.9451		
	(0.0260)	(0.0261)		
ρ^b	0.2565	0.2494		
	(0.0297)	(0.0300)		
c			0.5417	0.7262
			(0.0777)	(0.0482)
oil price	0.0011	0.0015	0.0080	0.0069
	(0.0102)	(0.0101)	(0.0121)	(0.0126)
REER	0.1046	0.1013	0.1008	0.0968
	(0.0101)	(0.0102)	(0.0102)	(0.0102)
ω^w			0.2429	0.1466
			(0.1678)	(0.0671)
ω^b			0.0681	0.1162
			(0.0293)	(0.0623)
B^w			0.0904	0.0168
			(0.1287)	(0.0128)
B^b			0.0406	0.0862
			(0.0109)	(0.0316)
A			0.8149	0.7986
			(0.0917)	(0.0897)
ω^σ	-0.1319	-0.0994	-0.1451	-0.1092
	(0.0430)	(0.0732)	(0.0463)	(0.0721)
A^σ	0.7492	0.8361	0.7301	0.8267
	(0.0591)	(0.0929)	(0.0659)	(0.0943)
B^σ	0.0290	0.0665	0.0271	0.0862
	(0.0026)	(0.0143)	(0.0027)	(0.0316)
λ		27.9616		27.9470
		(5.7398)		(5.6734)
logLik	-7794.4	-7749.0	-7769.2	-7723.6
$AICc$	15606	15518	15565	15477

Figure 4 presents the plots of the estimated time-varying volatility σ_t^2 for the Gaussian and Student's t models. In both cases, the overall volatility level appears to significantly decline after 2005. The declining volatility can possibly be explained by the large increase of export growth in 2005. However, other country-specific factors may have contributed to the moderation of growth volatility such as the introduction of inflation targeting in economic policy or the implementation of fiscal rules. Therefore, further research would be required in order to identify the specific factors underlying the moderation of growth volatility. Some short-term increases in the estimated time-varying volatility appear to be associated with some specific economic and financial crises in specific countries. For instance, the Mexican tequila and Asian crises in the periods 1994/1995 and 1997/1998 anticipate the largest spikes in volatility. The tequila crisis was triggered by a sudden devaluation of the Mexican peso of around 15 percent on December 20 of 1994. This devaluation has prompted foreign investors to re-adjust their investment portfolios by reducing exposure to Mexico and other LA countries, leading to a significant capital outflow. Similarly, the Asian crisis was triggered by currency depreciation that caused stock markets to collapse in Thailand, the Philippines, Malaysia and Indonesia. This crisis has impacted Latin America, primarily, through trade channels and the financial system. In particular, in 1995 the Asian countries involved in the crisis accounted for around 15 percent of world imports of agricultural raw materials, minerals, metals and petroleum, which are principal export products of LA countries. The depression of external demand has caused a significant reduction in prices, leading to weaker economic outlooks for LA countries. We refer the reader to Edwards (1998) for a much more detailed discussion on the economic impact of both crises. In recent years, the financial crisis of 2008/2009 and the fall of commodity prices in 2014/2015 appear to precede temporary increases in volatility. This may have been caused by the financial crisis in the US which has impacted LA countries through trade channels by lowering the external demand for export products, resulting in capital outflows due to lower economic outlooks.

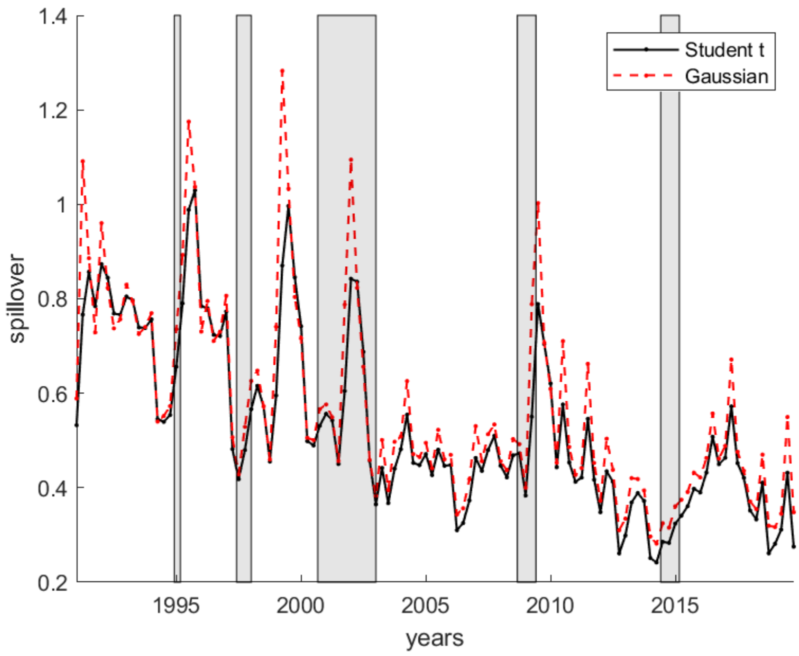

Figure 4: Time-varying volatility σ_t^2 for the Gaussian model (red dashed line) and the Student's t model (black solid line). The five shaded areas are as in Figure 2.

5.3 Spillovers and labor efficiency

The growth spillovers ρ_t^w and ρ_t^b aim at capturing productivity improvements due to both domestic and international trade interactions, respectively. Given economic factors such as inappropriate technologies, policy-induced barriers to technology adoption, and within-country misallocations across sectors (possibly caused by policy distortions), countries may not benefit from growth spillovers generally. As a result, productivity disparities widen with respect to the technological frontier; see the discussion in Gancia and Zilibotti (2009).

The common approach for estimating the distance to a technological frontier is based on determining the ratio of output per worker of a given country, with respect to a high-tech economy such as the United States (US). In the discussion below, we refer to this ratio as *labor efficiency*. Therefore, when spillovers are positively correlated with labor efficiency, there is technology adoption emerged from either domestic or international trade. Otherwise, market inefficiencies are constraining growth benefits. The labor efficiency ratio is defined as follows

$$L_{i,t} = \log\left(\frac{Y_{i,t}/H_{i,t}}{Y_{US,t}/H_{US,t}}\right) \tag{22}$$

where $Y_{i,t}$ is the output in constant 2010 dollars and $H_{i,t}$ is the number of employed people, at time t and in country i, with $i =$ US referring to these variables for US. When assuming equal Domar weights among economies, the labor efficiency ratio reflects the weighted sum of productivity ratios across sectors ($Z_{i,j,t}/Z_{US,j,t}$), compare equation (4). The labor efficiency ratio in Latin America has continuously declined over the 1995Q1-2019.Q4 period. This decline has been primarily attributed to the lack of technological progress rather than unperformed contribution of production factors (Restuccia and Roggerson (2008), Cole et al. (2005)).

Whether the lack of technological adoption can be attributed to domestic inefficiencies or international market distortions is an unresolved question. We attempt to provide some insights with the aim to answer this question by adopting a linear regression model with the *labor efficiency* ratio as the dependent variable and with between and within spillovers (together with intercept, time trend and seasonal dummies) as the explanatory variables. Table 4 presents a summary of the main regression results (upper panel) for each country. The between spillovers are positively correlated with labor efficiency in Latin America, in particular for the countries Argentina, Colombia and Peru. The pooled regression estimate (over all six countries) is 0.032 and strongly significant. Furthermore, the within spillovers are negatively correlated with labor efficiency, in particular for the countries Argentina, Brazil and Peru. The pooled regression estimate is -0.064 and also significant. Ceteris paribus, the negative estimates for within spillovers reveal some level of domestic market inefficiencies which prevent to exploit growth benefits from inter-sectoral interactions. The estimation results are fairly robust. In the lower panel of Table 4, the regression results are presented for the same regression model, with the yearly lagged labor efficiency ratio ($t-4$) added as an explanatory variable. The pooled within spillover estimate remain negative.

Table 4: Regression estimates and their robust (sandwich) standard errors in parenthesis. The panel regression model has the quarterly labor efficiency ratio $L_{i,t}$ as dependent variable, with between and within spillovers as explanatory variables, and with Student's distributed errors. The results in the upper panel are for this regression model that also include trend and seasonal dummies (estimates not reported) as explanatory variables. The results in the lower panel are for the same model but with the yearly lagged dependent variable ($L_{i,t-4}$ as an additional explanatory variable. The sample period is 1995.Q1 – 2019.Q4. The estimates are presented for each country and the pooled estimates over all countries are presented in column "LA". The maximized log-likelihood (logLik) and the Akaike information criteria corrected for finite samples (AICc) are also reported.

	LA	Argentina	Brazil	Chile	Colombia	Mexico	Peru
Intercept	-0.7726	-0.4706	-0.7154	-0.6744	-1.1401	-0.7213	-1.7198
	(0.0359)	(0.1201)	(0.0489)	(0.0393)	(0.2028)	(0.0546)	(0.1056)
Between	0.0316	0.1186	0.0181	0.0219	0.1137	0.0005	0.0777
	(0.0104)	(0.0364)	(0.0155)	(0.0110)	(0.0531)	(0.0139)	(0.0299)
Within	-0.0644	-0.1716	-0.1379	-0.0385	-0.0939	0.1102	-0.1417
	(0.0367)	(0.1279)	(0.0533)	(0.0396)	(0.2037)	(0.0558)	(0.1086)
logLik	-253.0	-150.2	-240.9	-249.3	-89.5	-212.6	-155.9
AICc	5.3	3.3	5.1	5.3	2.1	4.5	3.2
	LA	Argentina	Brazil	Chile	Colombia	Mexico	Peru
Intercept	-0.4580	-0.0707	-0.5887	-0.3822	-0.0476	-0.2423	-0.4585
	(0.0865)	(0.1015)	(0.0903)	(0.0701)	(0.1379)	(0.0765)	(0.1087)
$L_{i,t-4}$	0.4133	0.6293	0.2277	0.3516	0.8962	0.5942	0.7316
	(0.0966)	(0.0659)	(0.0902)	(0.0865)	(0.0544)	(0.0774)	(0.0489)
Between	0.0192	0.0645	0.0097	0.0255	-0.0073	-0.0001	0.0306
	(0.0099)	(0.0247)	(0.0161)	(0.0077)	(0.0167)	(0.0107)	(0.0144)
Within	-0.0513	-0.2112	-0.0814	-0.0812	-0.1565	-0.0257	-0.0842
	(0.0350)	(0.0962)	(0.0501)	(0.0302)	(0.0946)	(0.0422)	(0.0524)
logLik	-251.4	-169.9	-236.1	-262.9	-164.7	-233.8	-214.6
AICc	5.5	3.8	5.2	5.7	3.7	5.1	4.7

The positive estimates for the regression coefficients of the between spillovers confirm the hypothesis of technological adoption from trade interaction; see the discussions in Amiti and Konings (2007), Grossman and Helpman (1991) and Pavcnik (2002). Furthermore, the finding of the negative estimates for the coefficients of the within spillover is consistent with the results presented in Caliendo et al. (2021). These results strongly suggest that internal frictions (affecting transactions across sectors within countries) are more relevant than external frictions (affecting transactions across countries) for explaining world growth dynamics. The overall finding is that the economic growth in Latin America is positively correlated with technological progress emerged from international trade, as suggested by the between spillover results. Also, the inter-sectoral interactions within countries are growth reducing, and, hence, are suggesting that market distortions prevent technological progress.

6 Conclusion

We have developed an econometric spatial model with time-varying dependence parameters for the analysis of trade within a multi-country and a multi-sectoral economy. A reduced-form econometric framework is derived from the economic theory of a production network model. The time-varying dependence parameters can be attributed to to domestic (*within*) and international trade (*between*) linkages, and for different levels of data aggregation. The multivariate linear model can be based on either Gaussian or Student's t error distributions. The model parameters are estimated by standard maximum likelihood methods. It is argued that the resulting estimates are consistent and asymptotically normal. These asymptotic properties are verified for small-samples in a Monte Carlo study.

In the empirical study, we analyse the growth effects of intra-regional trade in six Latin American countries. The estimation results suggest that *i*) spillovers emerged from trade interactions (*between*) configure an important factor for explaining growth dynamics, and *ii*) the importance of spillovers emerged from domestic (*within*) linkages has declined. The former is associated with an increase on productivity levels, while the latter is connected with domestic labor market rigidities. In addition, our estimation results provide strong evidence of a continuous decline in growth volatility after the increase on export growth in 2005. Finally, we believe that our proposed methodology configures an important baseline for other economic analysis beyond trade, in topics such as migration, capital flows, economic disparities and income convergence.

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Appendix

A The equilibrium value for the Domar weight

The equilibrium value for the Domar weight in equation (6) can be alternatively expressed as

$$\eta_{i,j} s_{i,j,t} = \beta_{i,j} + \sum_{k=1}^{J} \kappa_{i,k,j} s_{i,k,t} + \sum_{v \neq i=1}^{N} \sum_{k=1}^{J} \kappa_{v,k,j}^{i} R_{v,j,t}^{i} s_{v,k,t}, \tag{A23}$$

where $\eta_{i,j} = \left[1 + \sum_{k=1}^{J} \varphi_{i,j,k}(1 - x_{i,j,k})\right]$, $\kappa_{i,k,j} = \varphi_{i,k,j} x_{i,k,j}$, $\kappa_{v,k,j}^{i} = \varphi_{v,k,j}(1 - x_{v,k,j})\lambda_{v,i}$, and $R_{v,j,t}^{i} = \frac{(Z_{v,j,t})^{-\alpha_{v,j}}}{(Z_{i,jt})^{-\alpha_{i,j}}}$.

The equivalent matrix representation is given by

$$s_t = \Upsilon_t^{-1}\delta, \tag{A24}$$

with $s_t = \{s_{1,1,t}, \ldots, s_{1,J,t}, \ldots, s_{N,1,t}, \ldots, s_{N,J,t}\}'$ a vector collecting the Domar weights, while $\gamma = \{\beta_{1,1}, \ldots, \beta_{1,J}, \ldots, \beta_{N,1}, \ldots, \beta_{N,J}\}'$ such that $\Upsilon = \{\psi_{n,m}\}$ is a $NJ \times NJ$ matrix, where $\psi_{n,m} \leq 0$ for all $m \neq n$, $1 \leq n$, $n \leq NJ$. Therefore, Υ is an M-matrix, with positive diagonal values, hence, the elements of its inverse are positive integers (see Perron-Frobenius Theorem). The Υ matrix is represented as follows

$$\Upsilon_t = \begin{pmatrix} \eta_{1,1} - \kappa_{1,1,1} & -\kappa_{1,2,1} & \ldots & -\kappa_{1,J,1} & -\kappa^1_{2,1,1}R^1_{2,1,t} & \ldots & -\kappa^1_{N,J,1}R^1_{N,1,t} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -\kappa_{1,1,J} & \ldots & \ldots & \eta_{1,J} - \kappa_{1,J,J} & -\kappa^1_{2,1,J}R^1_{2,J,t} & \ldots & -\kappa^1_{N,J,J}R^1_{N,J,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ -\kappa^N_{1,1,1}R^N_{1,1,t} & \ldots & \ldots & \ldots & \eta_{N,1} - \kappa_{N,1,1} & \ldots & -\kappa_{N,J,1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\kappa^N_{1,1,J}R^N_{1,J,t} & \ldots & \ldots & \ldots & \ldots & \ldots & \eta_{N,J} - \kappa_{N,J,J} \end{pmatrix}, \tag{A25}$$

where it is assumed that the condition $\eta_{i,j} - \kappa_{i,j,k} > 0$ holds, for any pair $\{i, j, k\}$. Hence, the model solution for equation (A24) can be represented by

$$s_{i,j,t} = \sum_{\tau=1}^{N}\sum_{k=1}^{J} a^{i,j}_{\tau,k,t}\beta_{\tau,k}, \tag{A26}$$

where $a^{i,j}_{\tau,k,t}$ is the corresponding element of Υ_t^{-1} with i indicating the row number and other indices selecting the appropriate column.