Adding Space to the International Business Cycle

Luis Servén, Girum Dagnachew Abate

PII: S0164-0704(20)30137-3
DOI: https://doi.org/10.1016/j.jmacro.2020.103211
Reference: JMACRO 103211

To appear in: *Journal of Macroeconomics*

Received date: 14 April 2019
Revised date: 21 February 2020
Accepted date: 30 April 2020

Adding Space to the International Business Cycle*

Luis Servén[a,†], Girum Dagnachew Abate[b]

[a]CEMFI, 28014 Madrid, Spain
[b]The World Bank Group, Washington, DC, 20433 USA

February 21, 2020

*We are indebted to an anonymous referee for extremely valuable comments. We also thank Paul Elhorst for useful suggestions, and Wei Shi for generously sharing his computer code. However, they are not responsible for any errors. The views expressed here are only ours and do not necessarily reflect those of the World Bank, its executive directors, or the countries they represent.

†Corresponding author. Email addresses: lserven@cemfi.es (Luis Servén), gabate@worldbank.org (G. Abate).

Adding Space to the International Business Cycle

February 21, 2020

Abstract

Growth fluctuations exhibit substantial synchronization across countries, which has been viewed as reflecting a global business cycle driven by shocks with worldwide reach, or spillovers resulting from local real and/or financial linkages between countries. This paper brings these two perspectives together by analyzing international growth fluctuations in a setting that allows for both global shocks and spatial dependence. Using annual data for 117 countries over 1970-2016, the paper finds that the cross-country dependence of aggregate growth is the combined result of global shocks summarized by a latent common factor and spatial effects accruing through the growth of nearby countries – with proximity measured by bilateral trade linkages or geographic distance. The latent global factor shows a strong positive correlation with worldwide TFP growth. Countries' exposure to global shocks is positively related to their openness to trade and the degree of commodity specialization of their economies, and negatively to their financial depth. Despite its simplicity, the empirical model fits the data well. Ignoring the cross-country dependence of growth, by omitting spatial effects or common shocks (or both) from the analysis, leads to a marked deterioration of the empirical model's in-sample explanatory power and out-of-sample forecasting performance.

Keywords: World business cycle, common factors, spatial dependence
JEL classification: F44, C23, F62

1 Introduction

The international synchronization of business cycles has long attracted academic and policy interest. From the academic viewpoint, understanding the factors behind the cross-country comovement of output can help shed light on the empirical validity of different classes of theoretical models. From the policy perspective, quantifying the degree of business cycle commonality is a primary consideration from the point of view of optimal currency areas and, more broadly, to assess the merits of independent stabilization policies.

An extensive empirical literature views the international comovement of growth as the reflection of a global business cycle driven by shocks affecting a multitude of countries. Following the contribution of Kose, Otrok and Whiteman (2003), a number of studies model the cycle as the combined effect of a set of global and region (and, in some cases, sector-specific) latent common factors; see e.g., Kose, Otrok and Prasad (2012), Crucini, Kose, and Otrok (2011), Mumtaz, Simonelli and Surico (2011), and Karadimitropoulou and Leon-Ledesma (2013). This literature finds that the international business cycle can account for a major portion of cyclical GDP fluctuations – as much as 40 percent of their variance in the case of G7 countries, according to the results of Kose, Otrok and Whiteman (2003).

Another strand of empirical literature stresses growth interdependence arising from economic linkages between countries or regions. This is the approach taken by the extensive Global VAR (GVAR) literature pioneered by Pesaran, Schuermann and Weiner (2004), and recently surveyed by Chudik and Pesaran (2016), which underscores the real and financial dependence across countries that arises from their bilateral goods and assets trade. The same basic mechanisms feature in several papers taking a spatial perspective on growth empirics. Thus, Ho, Wang and Yu (2013) find evidence of growth spillovers due to bilateral trade linkages between OECD countries. In the context of a Solow model, they conclude that the estimated rate of convergence is significantly higher once those spatial links are taken into account. Likewise, Wang, Wong and Granato (2015) find that the comovement of growth across countries is well explained by the geographic distance between them.

These two empirical literatures share a common concern, namely the dependence of economic growth across countries and regions. But methodologically they take very different views. The first literature stresses shocks with global reach, affecting all countries or regions under consideration. The second literature puts the emphasis on the linkages generating dependence between particular countries or regions. The two views roughly correspond to the distinction between strong and weak cross-sectional dependence, respectively. Strong dependence arises from pervasive common shocks. In turn, weak dependence between specific countries or regions primarily reflects their economic and/or geographic proximity.[1] Strong dependence is typically analyzed with factor models (as done, for example, by Kose, Otrok and Whiteman (2003)), while weak dependence is typically analyzed with spatial models highlighting geographic or economic distance (as in, e.g., Ho, Wang and Yu (2013)).

So far, the empirical literature on growth interdependence and international business cycles has taken into account one or the other form of dependence – but not both. However, identifying correctly the type of cross-sectional dependence at work can be quite important for estimation of and inference on empirical growth models. While details may depend on the specific model under consideration, ignoring strong dependence in the estimation when it is present will generally lead to inconsistent estimates if the omitted common shocks are correlated with the model's regressors (Pesaran and Tosetti (2011)). Conversely, introducing common factors in the estimation when only weak dependence is at play may similarly yield inconsistent estimates (Onatski (2012)). In turn, the consequences of neglecting spatial dependence when it is present hinge on its precise form. If spatial dependence accrues through the

[1]Strong and weak cross-sectional dependence can be formally defined in different ways. One commonly-used definition bases the distinction between them on the rate at which the largest eigenvalue of the covariance matrix of the cross-section units rises with the number of units; see Bailey, Kapetanios and Pesaran (2015).

model's error term, ignoring it will only cause loss of efficiency. However, ignoring spatial dependence in the dependent variable and/or the independent variables may yield biased and inconsistent estimates of the parameters of the remaining variables (LeSage and Pace (2009)).

In reality, however, the two forms of dependence are likely to be simultaneously present. Indeed, growth in a given country is likely to be affected by both global shocks and shocks to economically nearby countries – with closeness defined by bilateral trade intensity, financial linkages, and so on. The main contribution of this paper is to bring both perspectives together. We analyze the international comovement of GDP growth in a sample comprising over a hundred advanced and emerging countries, using an encompassing empirical framework including both spatial effects and common factors. This allows us to assess quantitatively the respective roles of strong and weak cross-sectional dependence in the observed patterns of GDP growth across the world, and to illustrate the consequences of ignoring either (or both) of them. To our knowledge, only Bailey, Holly and Pesaran (2016), who examine the patterns of house prices across U.S. metropolitan areas, and Vega and Elhorst (2016), who study regional unemployment trends across the Netherlands, have employed a similarly encompassing approach.

We assume that spatial interactions between countries occur through growth itself. This seems a natural way to model the linkages between national economies, and is the same approach followed by Ho, Wang and Yu (2013), as well as the GVAR literature on global business cycle dynamics. However, it also implies that the two-step estimation methods employed by Bailey, Holly and Pesaran (2016), who assume that the interaction occurs through the spatial error, are not applicable. Instead, we use the quasi-maximum likelihood (QML) estimator recently introduced by Shi and Lee (2017), which permits joint consideration of common factors and spatial dependence in a dynamic framework. Because the factors and their loadings are treated as parameters, and their number grows with sample size, they pose an incidental parameter problem that introduces asymptotic bias in the QML estimator. The bias correction developed by Shi and Lee

(2017) addresses this issue.

In light of the earlier literature, we experiment with two alternative specifications of the spatial weight matrix that summarizes interactions between countries. We use both a bilateral trade weight matrix, as done by Ho, Wang and Yu (2013), and a bilateral geographical distance weight matrix, as done by Wang, Wong and Granato (2015).

Our country sample contains both advanced and developing economies. The former are likely to be more deeply integrated than the latter in the international economy, and thus more exposed to the international business cycle. Hence we also estimate the empirical growth model on a subsample of 21 advanced countries. This allows us to assess differences between these countries and the rest regarding the extent and nature of cross-sectional dependence.

Estimation results using the two alternative specifications of the spatial weight matrix show that growth exhibits significant inertia, somewhat higher in the advanced country subsample than in the full sample. There is strong evidence of spatial effects, summarized by a significantly positive contemporaneous spatial lag, and a negative spatial-time lag, significant in the advanced-country sample. The implication is that local interactions are important to understand the international comovement of growth. However, the estimated spatial effects are substantially larger when modeling spatial dependence in terms of bilateral trade. Importantly, growth around the world also reflects a latent common factor, which we interpret as capturing the global business cycle. The factor shows a robust positive correlation with a measure of worldwide total factor productivity – as found by Crucini, Kose, and Otrok (2011) for G-7 countries – and with global commodity prices.

The model does a good job at accounting for the pattern of growth across the world and in particular its cross-country dependence. We find that the global cycle – as summarized by the common factor – and spatial interactions account for a substantial portion of the variance of GDP growth – around a quarter in the full sample, and over half in the advanced-country subsample.

Our results also speak to the determinants of countries' exposure to global shocks, an issue at the core of the policy debate. We find that the impact of the common factor on GDP growth is significantly bigger in countries with more open trade accounts, and those whose production structure is more tilted towards commodities. It is also significantly weaker in countries featuring larger financial depth.

Finally, the paper underscores the importance of properly addressing cross-sectional dependence, both strong and weak, in cross-country growth empirics. Ignoring it, by omitting both common factors and spatial effects, leads to a gross overstatement of the persistence of growth. It also weakens the estimated model's in-sample fit, as well as its out-of-sample forecasting ability. Including either the common factor or the spatial effects helps mitigate these problems, but does not fully solve them. Including both the factor and the spatial effects yields the best model performance, in terms of both in-sample fit and out-of-sample forecasting.

The rest of the paper is organized as follows. Section 2 introduces the factor-augmented dynamic spatial model of output growth employed in the paper. Section 3 presents the data. Section 4 reports the results, and Section 5 provides some conclusions.

2 Analytical framework

To study the international business cycle, we use a dynamic model that allows for both pervasive cross-sectional dependence through common factors and localized dependence through spatial linkages. We next describe the model and summarize our estimation approach.

2.1 A factor-augmented dynamic spatial model of growth

Let g_{it} denote the real output growth in country $i = 1, \ldots, n$ at time $t = 1, \ldots, T$, and let $g_t = (g_{1t}, ..., g_{nt})'$. We assume that g_t follows a spatial dynamic panel data model of the form:

$$g_t = \rho W g_t + \beta g_{t-1} + \lambda W g_{t-1} + \Psi f_t + V_t. \tag{1}$$

Thus, each country's real output growth is related to current real output growth in (economically) neighboring countries, Wg_t, where W is an $n \times n$ spatial weight matrix; lagged real output growth in the own country, g_{t-1}, as well as in neighboring countries Wg_{t-1}; a set of r time-varying unobserved factors f_t common to all countries; and a stochastic disturbance $V_t = (V_{1t}, ..., V_{nt})'$. The parameters λ, β and ρ are all scalars, while Ψ is an $n \times r$ matrix of factor loadings.

This general specification allows for both spatial dependence, unobserved common factors and growth persistence. Spatial dependence, embedded in the spatially-lagged dependent variable Wg_t as well as its time-lagged value Wg_{t-1}, reflects the effects of current and lagged real output growth of nearby countries on the real output growth of a particular country, see e.g Ho, Wang and Yu (2013) and Ertur and Koch (2007). The extent of spatial dependence is measured by the contemporaneous spatial autoregressive parameter ρ and the space-time lag coefficient λ.[2]. The relative contribution of each country to the overall spatial effect is measured by the spatial weight matrix W, which can be understood as providing a measure of economic proximity between countries.

In turn, the unobserved common factors f_t capture systemic shocks that affect real output growth across all countries. The $n \times r$ matrix of factor loadings Ψ measures the (possibly heterogeneous) effect of the factors on each country's growth. Finally, growth persistence is captured by the parameter β on the lagged endogenous variable.

Equation (1) nests various models as special cases. For example, in the absence of spatial dependence ($\rho = 0$ and $\lambda = 0$), equation (1) simplifies to a factor-augmented

[2]The parameter λ, termed 'diffusion parameter' by Shi and Lee (2017), captures spatio-temporal correlations in output growth that may result from partial adjustment (e.g., gradual responses to policy changes) or inter-temporal decision making by economic agents, see e.g., Tao and Yu (2012). These authors also show analytically that in such settings λ should typically be negative. Further, they also find that omitting a relevant spatial time lag can result in significant biases in regression estimates.

model relating real output growth to observable lagged growth plus latent common factors, see e.g. Kose, Otrok and Whiteman (2003), Jorg and Sandra (2016) or Moench, Ng and Potter (2013). Equation (1) can also be seen as a variant of the GVAR model of Chudik and Pesaran (2016) imposing constant β, λ and ρ across countries.

In these specifications, the spatial dependence between countries is parameterized by the $n \times n$ spatial weight matrix W. The matrix is assumed to be non-stochastic, with the properties (i) $W_{ij} \geq 0$ for $i \neq j$, and (ii) $W_{ij} = 0$ for $i = j$. The first property indicates that the elements of W are non-negative known constants. The second property states that countries are not neighbors to themselves. In empirical applications the weight matrix W typically is row-normalized, such that $\sum_{i \neq j}^{n} W_{ij} = 1$, see Anselin (1988).

Further, define $S = (I - \rho W)$. Assuming that S is invertible, and letting $A = S^{-1}(\beta I + \lambda W)$, equation (1) can be written as $g_t = A g_{t-1} + S^{-1}(\Psi f_t + V_t)$. Recurrent substitution yields

$$g_t = \sum_{h=0}^{\infty} A^h S^{-1}(\Psi f_{t-h} + V_{t-h}). \tag{2}$$

With a row-normalized spatial weight matrix W, the sequence $\{A^h\}_{h=0}^{\infty}$ is summable in absolute value, and the initial condition g_0 becomes asymptotically irrelevant when $T \to \infty$, provided the model's parameters lie in the region $R_s = \{(\rho, \beta, \lambda) : \beta + (\lambda - \rho)\omega_{min} + 1 > 0, \beta + \lambda + \rho - 1 < 0, \beta + \lambda - \rho + 1 > 0, \beta + (\rho + \lambda)\omega_{min} - 1 < 0\}$, where ω_{min} is the smallest characteristic root of the weight matrix W, see Shi and Lee (2017).[3]

Equation (2) helps trace out the impulse responses to a unit shock in a given country (i.e., a particular element of V_t) both over time and across countries, as will be discussed in Section 4.

[3] The parameter estimates reported below satisfy these restrictions in all cases.

2.2 Estimation approach

Estimation of the model (1) poses some special issues because of the simultaneous presence of common factors and spatial effects. Both features are also present in the empirical specification employed by Bailey, Holly and Pesaran (2016), who use a two-stage approach to estimate their model: they estimate the common factors and the model's parameters at the first stage, and the spatial effects at the second stage, with inference done ignoring the first-stage sampling errors. In their setting, however, the spatial effects accrue through the error term, while in (1) they accrue through the dependent variable. This makes the spatial effects endogenous, and implies that the two-stage estimation approach is not applicable. The reason is that ignoring the spatial effects in the first-stage estimation, as done by Bailey, Holly and Pesaran (2016), would yield inconsistent estimates.

Dealing with the endogeneity requires instead an instrumental-variable approach, such as the GMM-type estimator proposed by Kuersteiner and Prucha (2018), or maximum likelihood methods, such as the quasi-maximum likelihood (QML) estimators developed by Shi and Lee (2017) and Bai and Li (2018). However, in our setting QML estimation faces an incidental parameters problem arising from the need to estimate the unobserved common factors and their loadings, in addition to the more standard problem posed by the presence of spatial effects and predetermined regressors (the lagged dependent variable); see Bai and Li (2018) for details. As a result, the QML estimator may show significant bias, for which a suitable correction is needed.

In this paper we employ the bias-corrected QML estimator recently developed by Shi and Lee (2017), which deals with both sources of bias. In their study of regional unemployment across the Netherlands featuring a setting similar to ours, Vega and Elhorst (2016) also employ a QML estimator, but the bias correction they adopt addresses only the second source of bias.[4] We next provide a brief outline of our

[4]Rather than estimating the common factors, Vega and Elhorst (2016) use the national unemployment rate to summarize them, assuming that the individual regions are too small to affect the country-wide unemployment rate

estimation approach, and refer the reader to Shi and Lee (2017) for the full details.

In equation (1), let $Z_t = (g_{t-1}, Wg_{t-1})$. Define the parameters of the model as $\eta = (\delta', \rho)'$ with $\delta = (\beta, \lambda)'$, the unobserved common factors $F_T = (f_1, f_2, ...f_T)'$ and their loadings Ψ, and σ^2, the variance of the iid disturbance V_{it}. Then the quasi-log likelihood function of the model in equation (1) is

$$L(\eta,\, \sigma^2,\, \Psi,\, F_T) = -\frac{1}{2}log2\pi - \frac{1}{2}log\sigma^2 + \frac{1}{n}log|S| - \frac{1}{2\sigma^2 nT}\sum_{t=1}^{T}(Sg_t - Z_t\delta - \Psi f_t)' \times (Sg_t - Z_t\delta - \Psi f_t). \tag{3}$$

Dropping the constant term $-\frac{1}{2}log2\pi - \frac{1}{2}log\sigma^2$, this expression can be rewritten as

$$L(\eta,\, \Psi,\, F_T) = \frac{1}{n}log|S| - \frac{1}{2}log\left(\frac{1}{nT}\sum_{t=1}^{T}(Sg_t - Z_t\delta - \Psi f_t)' \times (Sg_t - Z_t\delta - \Psi f_t)\right). \tag{4}$$

While here the number of common factors r is assumed to be known, for the estimation it is determined using information criteria, as will be discussed below.

Due to the presence of the factors and their loadings, the number of parameters in the model increases with the sample size. Focusing on η as the parameter of interest, and concentrating out the factors and their loadings applying principal component analysis, the concentrated log-likelihood is

$$\begin{aligned} L(\eta) &= \max_{F_T \in \mathbb{R}^{T\times r}, \Psi \in \mathbb{R}^{n\times r}} L'(\eta, \Psi, F_T) \\ &= \frac{1}{n}log|S| - \frac{1}{2}log\, G(\eta), \end{aligned} \tag{5}$$

where $G(\eta) = \frac{1}{nT}\sum_{i=r+1}^{n}\mu_i(Sg - \sum_{k=1}^{K} Z_k\delta_k)(Sg - \sum_{k=1}^{K} Z_k\delta_k)'$, μ_i is the i^{th} largest eigenvalue of the symmetric matrix $(Sg - \sum_{k=1}^{K} Z_k\delta_k)(Sg - \sum_{k=1}^{K} Z_k\delta_k)'$, $g = (g_1, g_2, ..., g_T)$, K is the number of columns of Z_t (two in our setting), Z_k is an

– which can then be taken as exogenous. However, such an assumption is unlikely to hold in our setting, as our country sample includes some very large economies.

$n \times T$ matrix whose t-th column is just the k-th column of Z_t, and δ_k is the k-th element of δ. The QML estimator is derived from the optimization problem in equation (5). The estimate of the factor loadings Ψ is computed from the eigenvectors associated with the r largest eigenvalues of $(Sg - \sum_{k=1}^{K} Z_k\delta_k)(Sg - \sum_{k=1}^{K} Z_k\delta_k)'$. The estimate of F_T is obtained analogously by switching T and n.

The QML estimator of the regression coefficients is consistent and asymptotically normal. However, it is asymptotically biased owing to the incidental parameters problem already mentioned. To tackle this issue, Shi and Lee (2017) develop a bias correction that yields an asymptotically normal, properly-centered estimator. The estimation results reported below employ the bias-corrected estimator.

3 Data

We use a large cross-country growth data set drawn from the United Nations National Accounts database.[5] To circumvent potential outliers and data errors, we exclude (i) very small economies with total population less than 500,000, owing to their often extreme volatility; (ii) countries featuring any observations with annual real GDP growth in excess of 40%; and (iii) countries with standard deviation of real GDP growth exceeding 10%. This yields a balanced panel of 117 countries over the period 1970-2016. The sample countries account for more than 90% of world GDP in 2016. Because advanced countries feature higher trade and financial integration than other countries (see Kose, Terrones and Prasad (2004)), which likely affects their growth comovement, we consider separately a sub-sample of 21 advanced economies. The full list of countries is given in Table A1 in the appendix.

Real GDP is measured in constant U.S. dollars (expressed in international prices, base 2010), and annual real output growth is computed as the first difference of the log of real GDP.

[5] We employ GDP growth data from the United Nations National Accounts database because it reaches up to 2016. In contrast, PWT 9.0 data only reaches up to 2014. Over the common time sample, the correlation between the GDP growth rates derived from both sources exceeds 0.99.

The spatial weight matrix that connects cross-sectional units (countries) is an important element in the empirical implementation of the model. We measure the economic distance between each pair of countries by the magnitude of their bilateral trade, following the view that bilateral trade intensities capture economic interactions and shock spillovers across countries, so that countries that trade more are economically more connected, see e.g. Frankel and Rose (1998).

To construct the bilateral trade weight matrix, we use information on bilateral trade taken from the IMF Direction of Trade Statistics (DOT). Specifically, for a pair of countries $i \neq j$, entry i,j of the trade spatial weight matrix W is defined as

$$W_{ij} = \frac{Exports_{ij} + Imports_{ji}}{\sum_{K=1}^{K=N} Exports_{ik} + \sum_{K=1}^{K=N} Imports_{ki}},$$

where $Exports_{ij}$ denotes the exports from country i to country j, and $Imports_{ji}$ are the imports of country i from country j. Once W has been computed, it is rescaled dividing each of its elements by the sum of its corresponding row, so that the rows of the rescaled matrix sum to unity.[6]

Alternatively, following Ertur and Koch (2007), we use a weight matrix WD based on inverse squared distance. The elements of WD are defined (before row normalization) as

$$WD_{ij} = \begin{cases} 0 & \text{if } i = j \\ {d_{ij}}^{-2} & \text{otherwise,} \end{cases}$$

where d_{ij} is the great-circle distance between the capital cities of countries i and j.[7]

To assess the covariates of the common factors, we consider four candidate variables,

[6] Such row standardization of the weight matrix facilitates the interpretation of the model coefficients, see Anselin (1988).

[7] Here we follow the trade literature, in which distance between countries is typically measured by the distance between their respective capital cities; see e.g., Anderson and Wincoop (2004). The great-circle distance, the shortest distance between any two country capitals, is computed as: $d_{ij} = radius \times cos^{-1}[cos\,|long_i - long_j|\, coslat_i costlat_j + sinlat_i sinlat_j]$ where radius is the Earth's radius, and lat and $long$ are, respectively, latitude and longitude for country capitals i and j. The latitude and longitude coordinates for each of the country capitals in our sample were collected from the CEPII database.

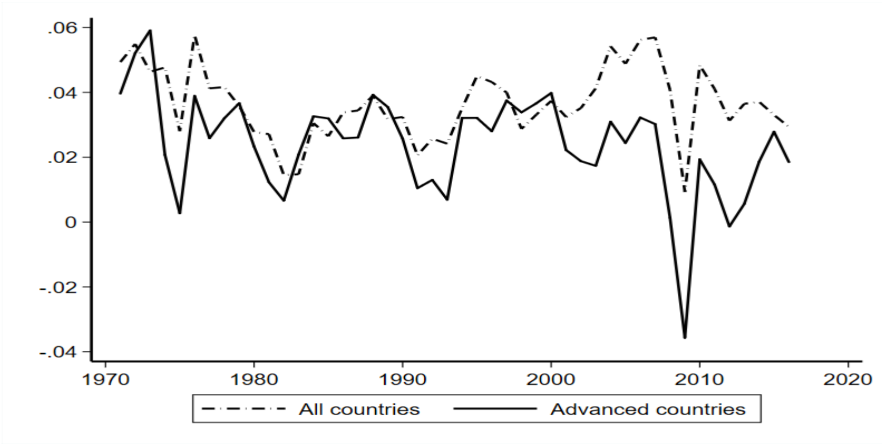
namely, (i) total factor productivity; (ii) policy uncertainty; (iii) the U.S. short-term real interest rate; and (iv) global commodity prices. Crucini, Kose, and Otrok (2011) find that total factor productivity is the leading driver of the business cycle of G-7 countries. They also find a relatively minor contribution of monetary policy. In turn, Baker and Bloom (2013) show that policy uncertainty plays an important role in driving business cycles. Barrot, Calderón and Servén (2018) find that commodity price shocks account for a major portion of the growth fluctuations of developing countries.

Total factor productivity (TFP) is computed from the standard Solow residual using capital and labor inputs, and is drawn from the Penn World Tables version 9.0. Policy uncertainty is measured using the U.S. policy uncertainty index of Baker, Bloom and Davis (2016). The U.S. real interest rate is taken from the Fred dataset. World commodity prices are measured by the World Bank's price index of nonfood commodities in real terms.

To assess the determinants of exposure to global shocks, we regress factor loadings on a set of variables capturing countries' policy and structural features, namely: (i) trade openness, measured as total exports plus imports as a percentage of GDP; (ii) financial openness, measured by the Chinn-Ito index of capital account openness; (iii) financial depth, measured by domestic credit to the private sector as a percentage of GDP; (iv) the extent of commodity specialization, measured by net real exports of commodities over GDP as in Leamer (1984, 1995); (vi) the size of the public sector, measured by government consumption as a percentage of GDP; and (vii) the size of the economy, as captured by total population.

Figure 1 depicts the time path of average real GDP growth for both the full and advanced country samples. The trends are similar in both cases, although growth is consistently higher in the former (3.6% on average over the entire sample period) than in the latter (2.3%). The figure also shows major recessions at the time of the oil shock of the mid 1970s as well as in 2008/09 following the global financial crisis. Average growth falls more sharply in the latter episode, and the fall is more severe for advanced

Figure 1: Average real output growth



countries (see also Kose, Otrok and Prasad (2012)).

As Figure 1 also shows, growth displays significant persistence, somewhat larger among advanced economies than among the rest. The mean of country-specific first-order autocorrelation coefficients of growth equals 0.30 in the full sample, and 0.34 in the advanced-country sample.

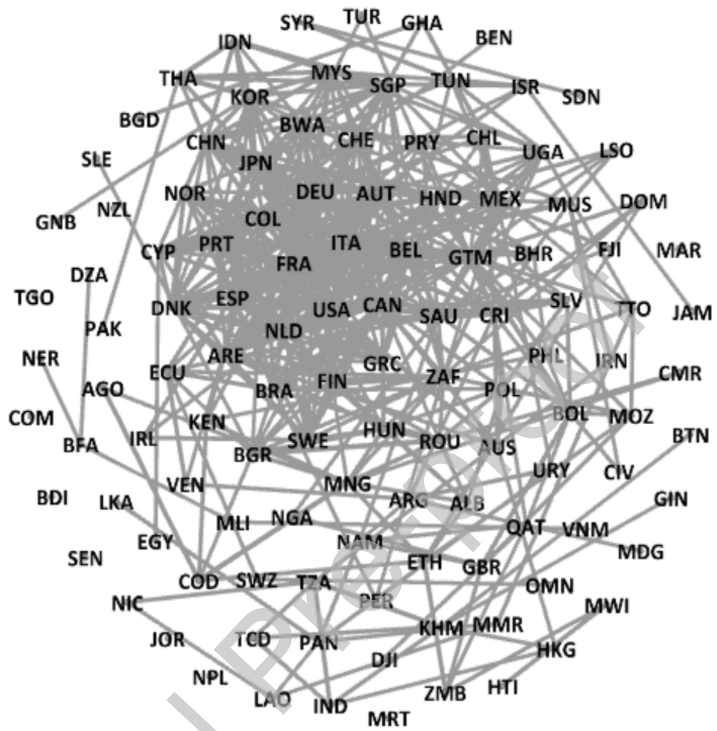
4 Empirical results

As a first step, we compute the pairwise correlation of real output growth across countries, and visualize it using network maps.[8] Figure 2 shows the network map of pairwise growth correlations for the full sample. The average and median correlation are, respectively, 0.126 and 0.088. To avoid cluttering the figure, we only depict those correlations above a threshold value of 0.4. In the network map, the correlation between two countries is indicated by the connecting line, and the position of the countries is determined by the magnitude of the pairwise correlations, such that countries that exhibit stronger correlations are located near each other. As shown, most of the advanced economies locate near each other. There is a cluster of countries featuring high pairwise correlations that comprises Austria, Belgium, Canada, France,

[8]Some studies, such as Ductor and Leiva-Leon (2016), use pairwise growth correlations to study business cycle interdependence.

Germany, Italy, Spain, Netherlands, USA and Colombia, among others. At the other extreme, several African countries (Togo, Comoros, Burundi, Senegal, Mauritania) exhibit relatively low connection to the system.

Figure 2: Real GDP growth correlation, all countries

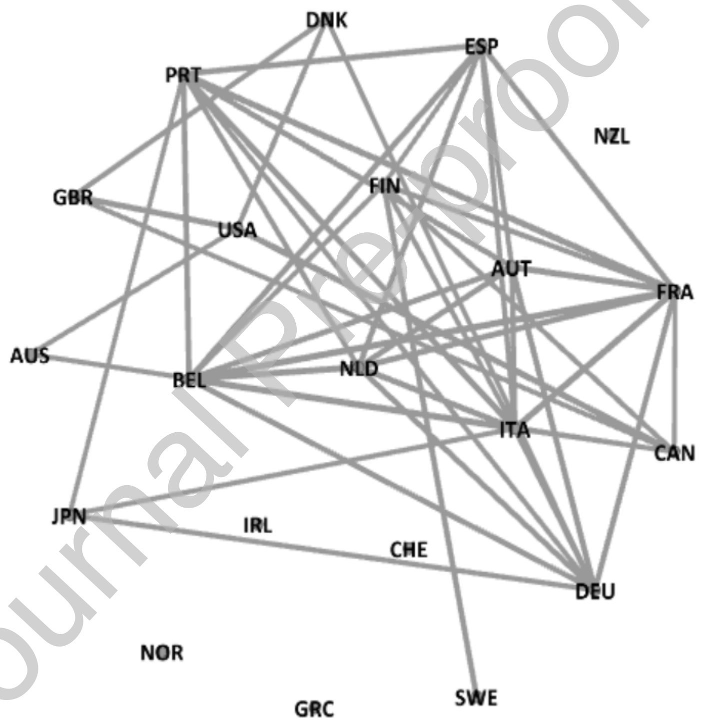


Notes: The pairwise correlation between two countries is indicated by their connecting line. Pairwise correlations less than 0.4 are dropped. If two countries are not connected in the graph, their pairwise correlation is less than 0.4. The list of countries and the corresponding codes are given in the appendix in Table A1.

Similarly, Figure 3 displays the network map of pairwise growth correlations for the advanced countries. The average and median correlation are, respectively, 0.478 and 0.470. Because pairwise correlations are generally higher among advanced countries than in the full sample, we use a higher threshold value of 0.6 in Figure 3. By this measure, each of the advanced countries is connected with at least one other country, except for Greece, Ireland, Norway, New Zealand, and Switzerland. European Union countries such as Belgium, Germany, France, the Netherlands, Portugal and Spain appear to be connected with a larger number of countries than the rest.

While the pairwise correlations summarized in Figures 2 and 3 provide a first hint of the extent of cross-sectional dependence of real output growth, a more formal assessment can be made using two suitable statistics. The first one is the cross-sectional dependence (CD) test statistic of Pesaran (2015), which is based on a simple average of pairwise correlation coefficients. The statistic is given by $\sqrt{\frac{nT}{n(n-1)}}\left(\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\hat{r}_{ij}\right)$, where the $\hat{r}_{ij}$ are the estimated pairwise correlation coefficients. Under the null hypothesis of weak cross-sectional dependence – that is, if cross-sectional dependence is either absent altogether or limited to a sufficiently small number of cross-sectional units – Pesaran (2015) shows that $CD \xrightarrow{d} N(0,1)$ as $n, T \to \infty$.

Figure 3: Real GDP growth correlation, advanced countries



Notes: The pairwise correlation between two countries is indicated by their connecting line. Pairwise correlations less than 0.6 are dropped. If two countries are not connected in the graph, their pairwise correlation is less than 0.6. The list of countries and the corresponding codes are given in the appendix in Table A1.

Rejection of the null of the CD test suggests the presence of strong (or pervasive) cross-sectional dependence, which can be further investigated with the help of the second statistic – the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). It is defined by the standard deviation of the cross-sectional average of the observations. Specifically, the exponent α is given by $Std.(\tilde{x}_t) = O(n^{\alpha-1})$, where $\tilde{x}_t = n^{-1}\sum_{i=1}^{n} x_{it}$ is a simple cross-sectional average of the observations pertaining to period $t = 1, ..., T$. The exponent α takes a value between 0 and 1. While no formal test is available, an estimate of α close or equal to 1 is taken to indicate strong cross-sectional dependence, of the type usually captured with (strong) factor models.[9]

Table 1 reports the Pesaran CD test statistic and the exponent of cross-sectional dependence of real GDP growth, for the full sample (left column) and the advanced-country sample (right column). The CD test statistic is above 40 for both samples, overwhelmingly rejecting the null. Table 1 also reports the exponent of cross-sectional dependence along with its approximate standard error, for both the advanced and full country samples. The estimated value is 1 in the advanced-country sample, and .96 in the full sample. Thus, in both cases the estimates point to the presence of strong common factors in the output growth data, consistent with the findings of, e.g., Kose, Otrok and Whiteman (2003).

Table 1: GDP growth: cross-sectional dependence

	All countries	Advanced countries
Pesaran CD statistic	42.223	43.134
(p-value)	(0.000)	(0.000)
Exponent of CSD	0.960	1.003
(standard error)	(0.029)	(0.058)
Number of countries	117	21

Notes: GDP growth is the first difference of the log of real GDP. 'Pesaran CD statistic' is the cross-sectional dependence statistic of Pesaran (2015). 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). The sample period is 1970-2016.

[9] In a general factor model setting the exponent of cross-sectional dependence can be interpreted as the rate at which the factor loadings (fail to) die off as cross-sectional sample size increases, see Bailey, Kapetanios and Pesaran (2015).

4.1 Model estimation results

In order to estimate the factor-augmented dynamic spatial model (1), we first need to determine the number of unobserved common factors. To do so, we compute the *IC*, *BIC* and *HQ* information criteria proposed by Choi and Jeong (2018) setting the maximum number of factors to 5.[10] The results are shown in Table 2. The upper panel of the table reports results for the full sample, and the bottom panel reports results for the advanced-country sample. For the full sample, both the *IC* and *HQ* criteria suggest one factor while the *BIC* criterion suggests zero factors. For the advanced country sample, the *BIC* and *HQ* criteria suggest one factor while the *IC* criterion suggests two factors (by a narrow margin). We opt for employing one factor in all the estimations below.[11]

Table 2: Model selection criteria

Criteria	Number of factors				
	All countries				
	0	1	2	3	4
IC2	0.000	**-0.053**	-0.046	-0.016	0.015
BIC	**1.005**	1.494	2.311	3.246	4.188
HQ	0.809	**-0.319**	-0.280	-0.204	-0.116
	Advanced countries				
IC2	0.000	-0.470	**-0.487**	-0.464	-0.292
BIC	0.144	**-0.053**	0.187	0.466	0.756
HQ	0.503	**0.293**	0.410	0.647	0.889

We turn to the main estimation results. Table 3 reports model estimates for the full sample (left panel) and the advanced country-sample (right panel). In each case, the two columns in the table correspond to the two alternative spatial weight matrix specifications – bilateral trade and bilateral inverse distance.

Consider first the full-sample results on the first two columns of the table. The

[10]Setting the maximum number of factors to 3 gives very similar results.

[11]Ductor and Leiva-Leon (2016) also employ a single factor to capture the common component of GDP growth across countries.

coefficient estimate of lagged output growth is positive and statistically significant in both specifications, indicating a significant degree of inertia of output growth.

Table 3: Estimation results

	All countries		Advanced countries	
Weight matrix	Trade	Distance	Trade	Distance
g_{t-1}	0.326	0.324	0.407	0.380
	(24.833)	(24.658)	(13.435)	(12.367)
Wg_t	0.344	0.110	0.742	0.192
	(11.777)	(5.139)	(33.994)	(3.884)
Wg_{t-1}	-0.073	0.024	-0.201	-0.233
	(-1.529)	(0.876)	(-5.090)	(-2.892)
Pesaran CD statistic	-0.172	-0.325	1.997	-1.194
(p-value)	(0.432)	(0.373)	(0.023)	(0.116)
Exponent of CSD	0.423	0.415	0.675	0.423
R^2	0.229	0.228	0.598	0.519
$\bar{R}^2$	0.205	0.202	0.565	0.484

Notes: GDP growth is the first difference of the log of real GDP. 'Pesaran CD statistic' is the cross-sectional dependence statistic of Pesaran (2015). 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). T-statistics in brackets. The sample period covers 1970-2016.

Turning to the spatial effects, the coefficient estimate of the contemporaneous spatial lag is positive and statistically significant. Its magnitude is much bigger under the trade weight matrix than under the distance matrix. The positive contemporaneous spatial lag indicates that higher output growth in a given country tends to raise growth of nearby countries in terms of both bilateral trade and geographical distance. This result, consistent with Ertur and Koch (2007) and Ertur and Koch (2011), implies that spatial spillover effects are important to understand growth, and countries cannot be treated as spatially independent. In turn, the space-time lag is insignificant under both weight matrices.

The factor-augmented dynamic model does a good job at capturing the cross-sectional dependence shown in Table 1. The CD test statistic given in the bottom panel of Table 3 finds little evidence of residual cross-sectional dependence.

Likewise, the exponent of cross-sectional dependence also indicates no strong cross-sectional dependence in the residuals.

The estimates from the advanced-country sample, shown in the third and fourth columns of Table 3, tend to follow the same sign and significance patterns of the full-country estimates. There are some differences, however. The estimated spatial effects are consistently larger, in absolute value, than in the full sample, likely reflecting the deeper economic linkages among advanced countries relative to the rest. Like in the full sample, the contemporaneous spatial lag is of much larger magnitude under the trade weight matrix than under the distance weight matrix. Still, under both specifications the CD statistic hints at residual cross-sectional dependence, more so when using the trade weight matrix. This might just reflect the known tendency of the CD test to over-reject when the cross-sectional dimension of the sample falls well short of its time dimension, see Pesaran (2015). However, another possible reason is that restricting the sample to just advanced countries may conceal significant indirect links between them arising from economic interaction with emerging and developing countries, which are not captured by the advanced-country spatial weight matrices. [12]

The bottom panel of Table 3 also reports the R^2 and its adjusted counterpart.[13] The model accounts for more than 20 percent of the variation of the dependent variable in the full sample, and over 50 percent in the advanced-country sample. In the full sample, the goodness of fit is similar under both specifications of the spatial weight matrix, while the trade matrix specification provides the better fit in the advanced country sample. By this measure, the model's explanatory power compares favorably with that of the multilevel factor model of Kose, Otrok and Whiteman (2003), which accounts for some 17 and 42 percent of the variance of growth of the median country in its world and G7

[12]This might happen if, for example, two advanced countries have the same trade partner(s) among emerging countries, but do not conduct any trade between themselves. A growth shock to the common emerging-market trade partner(s) will impact both advanced countries, in spite of the absence of a direct trade linkage. Empirically, non-advanced countries account for as much as half of the total merchandise trade of some of the major advanced economies, such as the U.S.

[13]R^2 is measured by the square of the correlation between the actual and predicted values of the dependent variable; see Elhorst (2014).

samples, respectively. [14]

Finally, the estimated models are able to account for the observed growth inertia. In the full sample, the country-specific first-order autocorrelation coefficients of the residuals average just -0.01 when the estimation is done using the trade weight matrix, and -0.03 when using the distance weight matrix. For the advanced-country sample, the average equals -0.05 in both cases. More formally, a panel test of the null hypothesis that the first-order autocorrelation of the residuals equals zero (Baltagi and Li (1995)) fails to reject the null in all cases. Under the null, the test statistic is distributed as a chi-square with one degree of freedom. In the full sample, its computed value was 1.65 (p-value 0.20) when using the trade weight matrix, and 1.71 (p-value 0.19) when using the distance weight matrix, while in the advanced-country sample the computed values were 0.22 (p-value 0.64) and 1.34 (p-value 0.25), respectively. This suggests that residual autocorrelation is not a concern.

For the specifications estimated in Table 3, Tables A3 and A4 in the appendix further report the correlation between the actual and fitted values by country for the full and advanced-country samples, respectively. The median value of the correlation is around .46 for the full sample and .75 for the advanced-country sample under both the bilateral trade and inverse distance weight matrices. However, there is considerable heterogeneity across countries, especially in the full sample. Guatemala, Romania, Spain and Congo exhibit correlations above 0.75 under both weight matrices, while a handful of emerging and developing countries, mostly in Sub-Saharan Africa (Benin, Fiji, Guinea Bissau, Madagascar, Morocco, Nepal and Senegal) show negative correlations. In the advanced country sample, 12 out of the 21 countries exhibit correlations above .7 under both the bilateral trade and the distance weight matrices. In contrast, Australia and New Zealand exhibit much lower correlations (around 0.3), indicating their (economic) remoteness within the system.

[14] These figures are based on their Table 4, and comprise the contribution of both the global and the regional factors in their model. Kose, Otrok and Prasad (2012) report very similar figures in their Table 1.

4.2 Transmission of spatial impacts

The fundamental implication of the dynamic spatial model is that a shock in a particular country affects growth not only in that country, but also in neighboring countries within the spatial system. Incorporating the spatial interaction effects helps better understand the nature and magnitude of spillover effects across countries. To illustrate the spatial spillovers implied by the estimates of the model, consider equation (1) rewritten as:

$$g_t = (I - \rho W)^{-1}(\beta I + \lambda W)g_{t-1} + (I - \rho W)^{-1}(\Psi f_t + V_t). \tag{6}$$

Recursive substitution shows that the effect h-periods ahead of a one-time shock to V_t is $\frac{\partial g_{t+h}}{\partial V_t} = [(I-\rho W)^{-1}(\beta I+\lambda W)]^h(I-\rho W)^{-1}$. The short-run effect is just $\frac{\partial g_t}{\partial V_t} = (I-\rho W)^{-1}$. Hence the impact of a shock hitting a particular country (i.e., a shock to a particular element of V_t) diminishes with distance at a rate that depends on the elements of the weight matrix W and the spatial coefficient ρ. It also declines over time at a rate that depends on λ, β and ρ. The larger (in absolute value) these parameters, the larger the eigenvalues of the transition matrix $[(I - \rho W)^{-1}(\beta I + \lambda W)]$, and the more persistent the effects of the shock.

For illustration, Figure 4 reports the impact on selected countries of one-time shocks to real output growth in the U.S., the U.K., Germany, Turkey, Mexico and Brazil. The graphs show the response obtained with the full-sample estimates using the trade weight matrix. In each case, the graphs show the contemporaneous response to a unit shock to output growth, and the dynamics over the subsequent three years.[15]

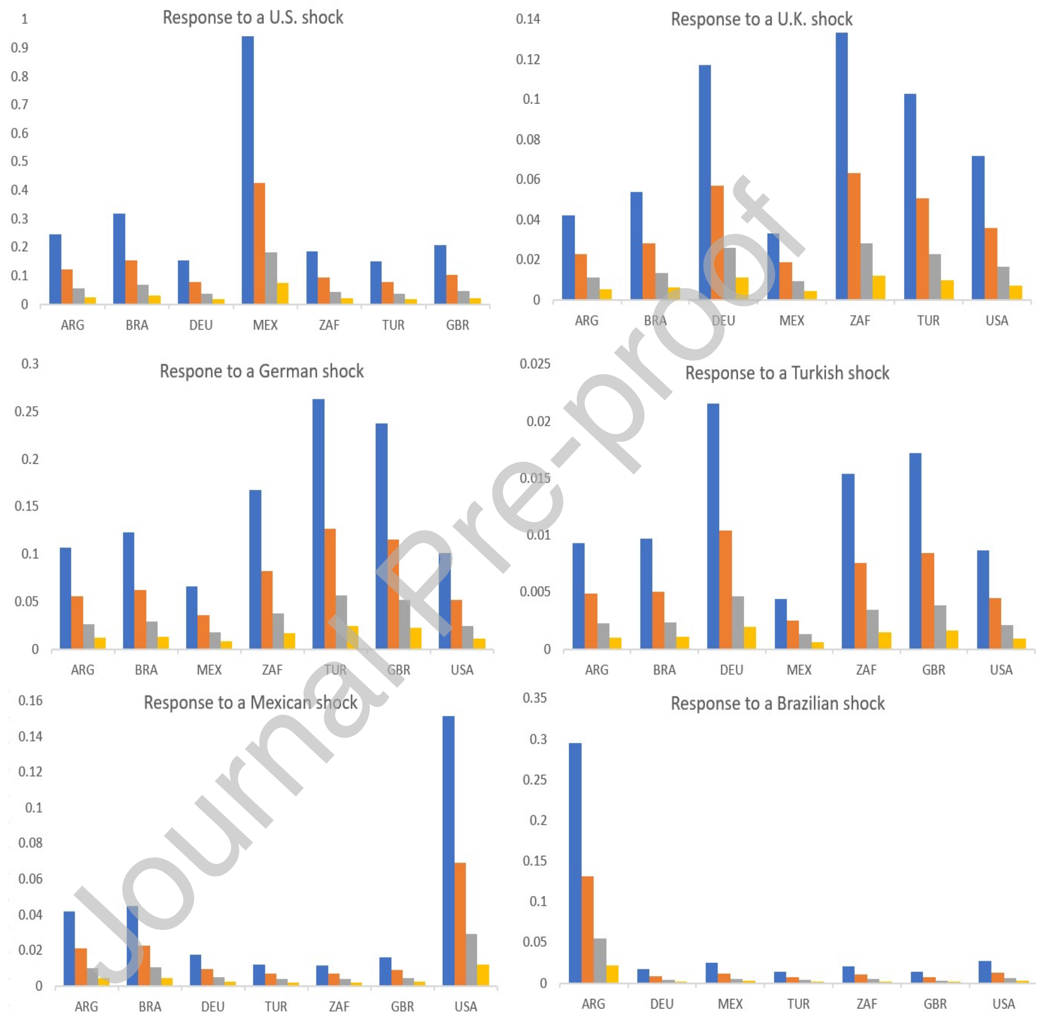
The short-run effects are, in some cases, fairly substantial. For example, a 1-percentage point shock to U.S. growth raises growth in Mexico by more than 0.9 percent. It also has a sizable impact on Brazil. In turn, a 1-percent shock to Brazil raises growth in Argentina by 0.3 percent, while a shock to Germany raises growth in Turkey by close to a quarter point.[16]

[15] The standard deviation of the growth residuals is .04.

[16] Under the distance specification of the weight matrix, impacts (not reported) are much smaller.

Convergence is monotonic and fairly rapid – after just three years, the impacts have declined to almost zero. The reason is that the eigenvalues of the transition matrix turn out to be fairly small in absolute value (under 0.4), thus implying only moderate persistence.

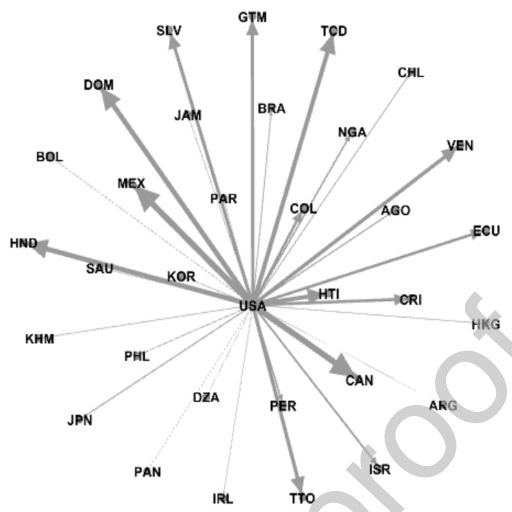
Figure 4: Dynamic spatial impacts



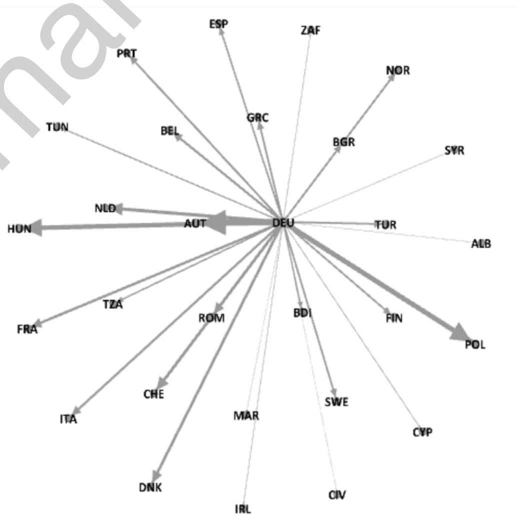
To further illustrate the propagation of output shocks, we compute the contemporaneous responses to a one-time shock to U.S. and German output growth using the full-sample estimates under the trade specification of the weight matrix. The results are summarized in Figure 5. In the figure, the direction of the arrows indicates the transmission of shocks from the source country to the (economically) neighboring

Figure 5: The short-run spatial transmission of shocks

(a) US



(b) Germany



Notes: The graph shows the short-run transmission of a one-time shock from the U.S. and Germany to other countries. The thickness of the arrows in the graph indicates the magnitude of the impact, i.e the thicker the arrow, the bigger the impact.

countries, while the thickness of the line indicates the magnitude of the shock spillovers. The closer a country is to the source country (in terms of the trade weight matrix), the bigger is the spillover. Canada and Mexico appear to be the most affected by a U.S. output growth shock. Shocks to Germany's growth have their largest impact on Austria, Hungary and Poland.

4.3 The common factor and the global business cycle

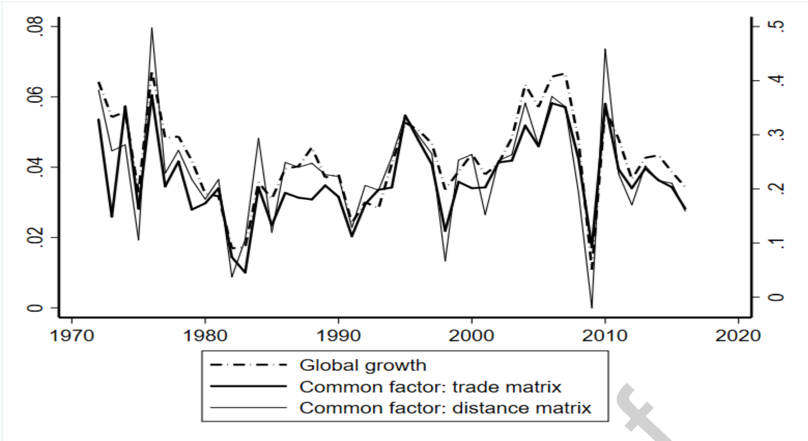
A crucial element of the empirical model is the unobserved common factor driving output growth around the world. Figure 6 depicts the common factors obtained from the model estimation under each of the weight matrices, for both the full and the advanced-country samples, along with the respective average growth rate of GDP. In the full sample, the common factor tracks average GDP growth very closely: the correlation of the factor with world GDP growth is .85 and .88 under the trade and distance weight matrices, respectively. The same happens in the advanced-country subsample under the distance matrix: the correlation of the common factor with average growth is .97. Under the trade matrix, however, the correlation is just .14, and instead the common factor shows fairly high correlation (.63) with the cross-sectional variance of growth. The conclusion is that trade linkages, by themselves, go a long way towards accounting for the cyclical comovement of advanced economies.[17]

Consistent with the findings of Kose, Otrok and Whiteman (2003), the swings in the estimated factors tend to reflect major economic episodes of the last four and a half decades – the recessions of the mid 1970s and early 1980s, the downturn of the early 1990s, and the financial crisis of 2008/09. For the full sample, the estimated common factors are very similar across the bilateral trade and distance matrix specifications in Table 3 – their correlation exceeds .89. For the advanced countries, the correlation is just .28.

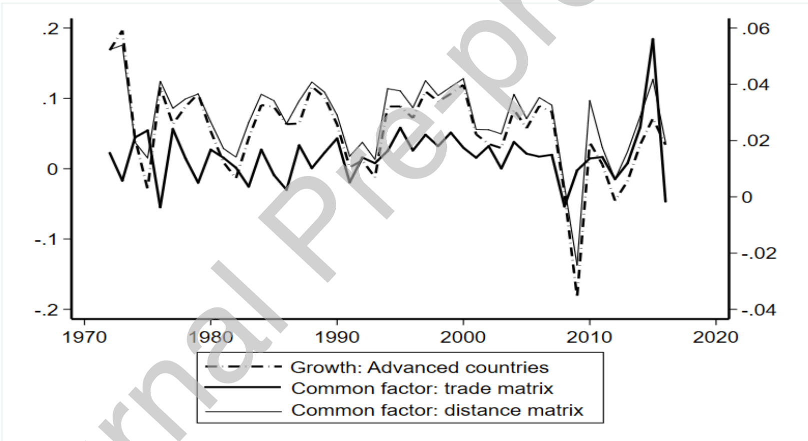
[17]To verify this claim, we re-estimated the model on the advanced-country subsample omitting the spatial effects. The correlation of the resulting common factor with average growth is .97. This indicates that the trade-based spatial effects largely substitute for the common factor in the task of fitting average growth fluctuations.

Figure 6: Output growth and common factor

(a) All countries



(b) Advanced countries



Kose, Otrok and Whiteman (2003) and Crucini, Kose, and Otrok (2011) also find a common factor behind worldwide and G-7 GDP growth, respectively. The latter paper also examines the drivers of the G-7 common factor, and concludes that productivity growth plays the leading role, in accordance with standard real business cycle models. In contrast, measures of monetary and fiscal policy, commodity prices, and the terms of trade are much less important. On the other hand, more recent work by Baker and Bloom (2013) and Baker, Bloom and Davis (2016) shows that policy uncertainty also plays a significant role in driving business cycles among advanced countries, with increased uncertainty resulting in declines in aggregate output, investment, and employment. In turn, Barrot, Calderón and Servén (2018) find that commodity price shocks accounts for a significant portion of the GDP fluctuations of emerging and developing countries.

Table 4: Factor covariates, trade and distance weight matrices

Variable	Trade weight matrix				
	I	II	III	IV	V
Δ TFP	4.531				3.958
	(6.704)				(4.282)
Uncertainty		-0.296			-0.126
		(-1.494)			(-1.380)
Real interest rate			-1.020		0.133
			(-3.009)		(-0.376)
Commodity price				0.193	0.221
				(2.611)	(4.177)
No. of obs.	43	32	45	45	30
R^2	0.517	0.086	0.110	0.097	0.710
	Distance weight matrix				
Δ TFP	5.643				4.998
	(5.539)				(2.990)
Uncertainty		-0.470			-0.176
		(-2.173)			(-1.280)
Real interest rate			-0.500		0.855
			(-1.061)		(1.475)
Commodity price				0.193	0.250
				(2.064)	(3.171)
No. of obs.	43	32	45	45	30
R^2	0.549	0.126	0.018	0.067	0.589

Notes: The dependent variable is the common factor from the full sample estimates in Table 3. Δ TFP is the first difference of log total factor productivity (TFP), Uncertainty is the log of the U.S. economic policy uncertainty index taken from Baker, Bloom and Davis (2016), Real interest rate is the U.S. real short-term interest rate, Commodity price is the log of commodity (non-food) price. T-statistics in brackets computed with heteroskedasticity and autocorrelation consistent (HAC) standard errors. The regressions include a constant.

To assess the covariates of the global business cycle in our much broader country sample, Table 4 presents regressions of the estimated common factor from the full country sample on total factor productivity, policy uncertainty, the U.S. short-term real interest rate, taken as a measure of global monetary conditions, and global non-food commodity prices. The upper panel reports the results obtained using as dependent variable the common factor derived from the model using the trade weight matrix, and the bottom panel reports the results obtained with the factor estimated when using the bilateral distance weight matrix.

The univariate regression results show that total factor productivity is positively correlated with the common factor, corroborating the findings of Crucini, Kose, and Otrok (2011) using data for G-7 countries. Moreover, the role of TFP growth is quantitatively large: it accounts for over half of the total variation of the common factor. Next, the uncertainty index, which is available only for a shorter time span, shows a negative sign, although it reaches statistical significance only under the trade weight matrix. In turn, the U.S. short-term real interest rate is negative correlated with the global factor under both configurations of the weight matrix, likely reflecting the action of supply-side monetary shocks (demand-side shocks should result in a positive sign). However, the regression coefficient is statistically significant under the trade matrix only. Lastly, global commodity prices show a significant positive correlation with the common factor. Finally, the last column of the table shows that when all four variables are considered jointly, they can account for 60-70 percent of the variation in the common factor – although the sample over which all regressors are available is admittedly short. However, only TFP growth and commodity prices remain statistically significant.

4.4 The exposure to the global business cycle

As already noted, the common factor driving output growth across the world can be interpreted as a summary representation of the global business cycle. A natural question is what determines countries' exposure to the cycle – or, in other words, the sensitivity of their output growth to global shocks.

In our model, the factor loadings measure the response of each country's output growth to the common shocks. For the full sample, the estimated loadings (shown in Figure 7(a)) are very similar across the two specifications of the weight matrix: their pairwise correlations exceed .96. The loadings are generally positive, with a few exceptions under the trade weight matrix, indicating that the global cycle affects the growth rate of almost all countries in the same direction. In the advanced-country sample, the correlation between the loadings obtained under the two alternative specifications of the weight matrix (shown in Figure 7(b)) is somewhat lower, but it still exceeds .85.

However, the magnitude of the loadings displays considerable variation across countries. In the full sample, the largest loadings belong to Botswana, Portugal and China when using the trade-based matrix, and Botswana, China and Singapore when using the distance weight matrix. In the advanced-country sample, the largest loadings correspond by far to Ireland, followed by Sweden and Spain under the trade-based weight matrix, and Portugal and Finland under the distance weight matrix.[18]

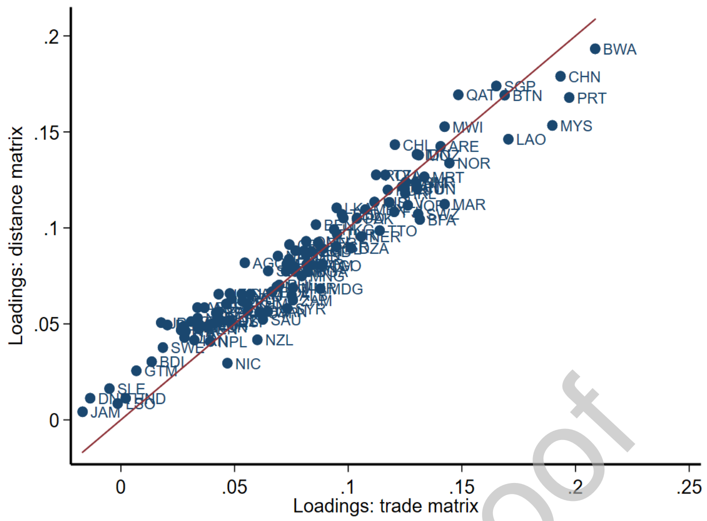
It seems plausible to expect the loadings to vary systematically with key features of countries' structural and policy framework – such as their degree of financial development and/or international integration.

To verify this conjecture, we regress the full-sample factor loadings on selected policy and structural indicators. Specifically, the variables we consider are trade openness, capital account openness, financial depth, commodity specialization, the relative size of the public sector, and country size.

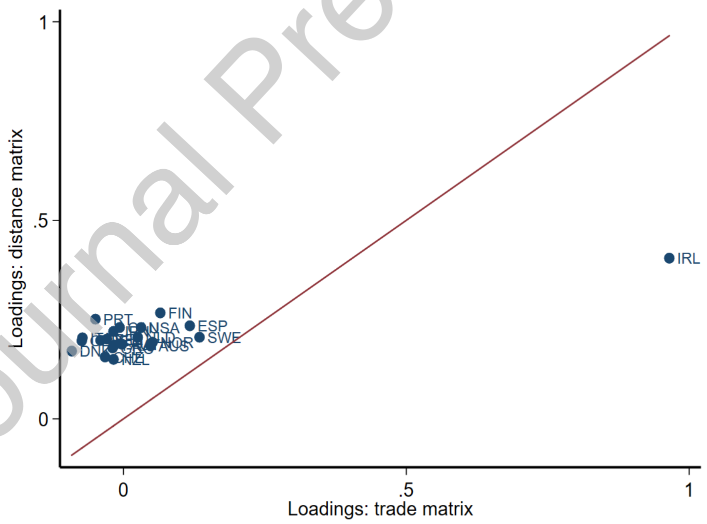
[18]Figure 7(b) shows that Ireland's loading is particularly large under the trade weight matrix. As already mentioned, under such configuration the estimated common factor is closely correlated with the cross-sectional variance of advanced-country growth. The variance peaks in 2015, as does the common factor shown in Figure 6(b) above. In that year, Ireland's real GDP growth rate topped 22 percent. The extreme value of Ireland's factor loading is largely a result of such extreme observation in the context of a sample of small cross-sectional dimension. Indeed, if the model is re-estimated using only the observations up to 2014, Ireland's loading under the trade weight matrix declines by half, and the correlation of the factor loadings with those obtained under the distance weight matrix rises to 0.99. The same happens with the correlation of the common factor obtained from such reduced time sample under the trade weight matrix with its counterpart under the distance weight matrix – it rises to 0.98.

Figure 7: Factor loadings

(a) All countries



(b) Advanced countries



On theoretical grounds, trade openness should raise business cycle interdependence by facilitating the transmission of shocks across countries, see Kose and Yi (2006), Ductor and Leiva-Leon (2016) and Barrot, Calderón and Servén (2018). In turn, financial openness plays in principle a more ambiguous role, as it might allow better diversification of real shocks but at the same time expose the economy to external financial disturbances. The same applies to domestic financial depth – it should help mitigate growth shocks, but it might also amplify large ones through the occurrence of financial crises. Next, a higher degree of commodity specialization should raise the economy's exposure to the global cycle, to the extent that the latter is partly driven by commodity price shocks. Indeed, Barrot, Calderón and Servén (2018) find that commodity-intensive developing economies are more vulnerable than the rest to both real and financial external shocks.

We also include public sector size, as measured by government consumption relative to GDP. The theoretical expectation is that a bigger public sector should help mitigate the impact of global disturbances. Finally, we also include average population as a proxy measure of country size. In their study of the cross-country comovement of aggregate consumption, Hevia and Servén (2018) find that larger economies reflect global consumption fluctuations more closely than smaller economies, because their income shocks make a larger contribution to global fluctuations than do shocks to the income of smaller economies – i.e., they are, to a larger extent, common shocks.

As the factor loadings do not change over time, the regressions only make use of the cross-sectional variation, and therefore the explanatory variables are measured by their respective average over the entire 46-year time sample. Over this time span, they have surely undergone major changes, which should tend to obscure their relationship with the loadings.

Table 5 reports the results from regressing the factor loadings on the explanatory variables. The upper panel reports results using the loadings obtained with the trade weight matrix, and the bottom panel reports the results obtained using the loadings obtained with the distance weight matrix. The univariate regressions show that exposure to the global business cycle significantly increases with countries' trade openness and commodity specialization, consistent with the results of Barrot, Calderón and Servén (2018), as well as country size, as found by Hevia and Servén (2018). This holds true as well in the regressions using all the variables jointly (shown in the final column of

Table 5: Loading covariates regression, all countries

Variable	Trade weight matrix						
	I	II	III	IV	V	VI	VII
Trade openness	0.019						0.021
	(2.146)						(1.847)
Financial openness		-0.014					-0.009
		(-0.876)					(-0.552)
Financial depth			-0.0002				-0.0003
			(-2.262)				(-2.496)
Commodity specialization				0.0002			0.0002
				(2.693)			(2.252)
Public sector size					-0.0003		0.0008
					(-0.298)		(0.698)
Population						0.000	0.000
						(2.590)	(4.626)
R^2	0.051	0.008	0.041	0.107	0.0008	0.038	0.258
	Distance weight matrix						
Trade openness	0.017						0.015
	(2.161)						(1.613)
Financial openness		-0.003					0.0009
		(-0.238)					(0.065)
Financial depth			-0.0001				-0.0002
			(-1.461)				(-1.991)
Commodity specialization				0.0002			0.0001
				(2.704)			(2.263)
Public sector size					-0.0005		0.0003
					(-0.669)		(0.337)
Population						0.000	0.000
						(3.279)	(5.107)
R^2	0.054	0.0006	0.018	0.115	0.004	0.046	0.247

Notes: The table shows regression of the factor loadings from the full sample estimates in Table 3 on the variables shown. Population is the average population (in millions) during 1970-2016. T-statistics in brackets computed with heteroscedasticity-consistent standard errors. The regressions include a constant.

the table), which also reveal that financial depth is negatively correlated with the factor loadings. In turn, financial openness and the size of the public sector are insignificant in both the univariate and the multivariate regressions.

4.5 Sensitivity analysis

Finally, we examine the sensitivity of our main results to alternative ways of modeling the cross-country dependence of output growth. Our methodological setting employs both common factors and spatial effects, in contrast with the earlier literature that opts for one or the other. We next assess how this choice affects our results. For this purpose, we re-estimate the model omitting the common factor and the spatial effects – first jointly and then in turn.[19]

The results are shown in Table 6. In the first column, cross-sectional dependence is ignored altogether, and common factors and spatial effects are both omitted – i.e., in terms of equation (1), we impose $\rho = \lambda = 0$ and $\Psi = \mathbf{0}$. In the second column, the model includes a common factor but no spatial effects (i.e., $\rho = \lambda = 0$). The last two columns rule out common factors (i.e., $\Psi = \mathbf{0}$) but allow for spatial effects described by the two alternative specifications of the spatial weight matrix. The top panel of Table 6 reports the results obtained with the full sample, and the bottom panel reports those obtained with the advanced-country sample.

The first column of Table 6 shows that ignoring cross-sectional dependence leads to distorted parameter estimates and to a marked deterioration of the model's empirical performance relative to that achieved when both spatial effects and common factors are allowed for (shown in Table 3). The parameter estimate on the lagged dependent variable almost doubles relative to that in Table 3. Moreover, in both samples the CD statistic and the exponent of cross-sectional dependence suggest (strong) residual dependence. In addition, the overall fit of the model, as measured by the R^2, is quite

[19]Ertur and Musolesi (2017) also compare the estimates obtained from a factor model with those obtained from a spatial model.

poor.

The second column of Table 6 adds a common factor but omits spatial effects. The parameter estimates of the lagged dependent variable are now much closer to those in Table 3. In the full sample, both the CD statistic and the exponent of cross-sectional dependence fall sharply indicating no cross-sectional dependence in the residuals. In the advanced country sample, on the other hand, both the CD statistic and the exponent of cross-sectional dependence also fall sharply relative to those in the first column, but they continue to hint at dependence among the residuals. Finally, the fit of the model shows a considerable improvement relative to the preceding column.

The last two columns of Table 6 report estimates including spatial effects, for each of the two versions of the spatial weight matrix we consider, but excluding the common factor. In all cases, the estimates of the parameter on the lagged dependent variable exceed the values shown in Table 3, likely overstating the persistence of growth. In turn, the spatial effects are strongly significant, except for the space-time lag under the trade matrix in the full sample. The cross-sectional dependence statistics show in general lower values than in the first column of Table 6, but the CD statistic still shows in all cases significant evidence against the null of weak dependence, suggesting that the spatial effects alone do not do enough to ameliorate the dependence in the data. Both the exponent of cross-sectional dependence and the CD statistic are higher in both samples under the distance weight matrix, which seems to imply that the problem is more acute in that setting. Lastly, the overall fit of the model, as measured by R^2, improves substantially relative to the first column with the addition of the spatial variables, but remains poorer than that of the factor-only model in the second column of the table. The same applies to the $\bar{R}^2$, even though the inclusion of the factor uses up a considerable number (i.e., $T + n$) of degrees of freedom.

Overall, comparison of Tables 3 and 6 shows that both the common factor and the spatial effects contribute to the model's empirical performance – they complement each other in their ability to account for cross-sectional dependence, and to track the variation

Table 6: Robustness checks

	All countries			
			Spatial only	
	None	Factor only	Trade	Distance
g_{t-1}	0.595	0.328	0.372	0.404
	(42.699)	(24.898)	(29.334)	(32.063)
Wg_t			0.557	0.278
			(26.184)	(14.460)
Wg_{t-1}			0.040	0.198
			(1.487)	(9.077)
Pesaran CD statistic	41.289	0.551	13.134	26.815
(p-value)	(0.000)	(0.291)	(0.000)	(0.000)
Exponent of CSD	0.889	0.473	0.597	0.802
R^2	0.139	0.222	0.175	0.153
$\bar{R}^2$	0.139	0.197	0.175	0.153
	Advanced countries			
			Spatial only	
	None	Factor only	Trade	Distance
g_{t-1}	0.691	0.384	0.436	0.446
	(17.452)	(12.323)	(14.692)	(14.869)
Wg_t			0.718	0.638
			(29.984)	(24.055)
Wg_{t-1}			-0.185	-0.136
			(-4.396)	(-3.185)
Pesaran CD statistic	38.375	2.580	2.582	7.533
(p-value)	(0.000)	(0.005)	(0.005)	(0.000)
Exponent of CSD	0.992	0.792	0.712	0.818
R^2	0.185	0.513	0.464	0.426
$\bar{R}^2$	0.185	0.476	0.463	0.425

Notes: GDP growth is the first difference of the log of real GDP. 'Pesaran CD statistic' is the cross-sectional dependence statistic of Pesaran (2015). 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). T-statistics in brackets. The sample period covers 1970-2016.

of the dependent variable. Inspection of the $\bar{R}^2$ suggests that the encompassing models in Table 3 provide the best fit to the data despite their consumption of degrees of freedom.

Table 7 reports further robustness checks on the specification of the empirical model. The first two columns add to the baseline specification in column 1 of Table 3 a spatial error term. The spatial error is significant only in the full sample under the distance weight matrix. Under such specification, the full-sample contemporaneous spatial lag coefficient becomes significantly negative, while the space-time lag coefficient becomes significantly positive. In all other cases, the spatial lag and space-time lag are insignificant. The CD statistic suggests the presence of residual cross-sectional dependence.

The third and fourth column employ two factors in the estimation, rather than the single factor used in the baseline specification. In light of the information criteria reported in Table 2, this would represent an overparameterization of the model. However, it is of little consequence for the parameter estimates, except perhaps for the coefficient on the lagged dependent variable in the advanced-country sample, which is somewhat larger than in Table 3. With an additional factor, the fit of the model improves relative to the Table 3 baseline. Still, in the advanced-country sample the CD statistics continue to show evidence against the null of weak cross-sectional dependence.

4.6 Forecasting performance

Properly accounting for cross-sectional dependence can help improve the accuracy and efficiency of growth forecasts. This has been illustrated by Bjornland, Ravazzolo, and Thorsrud (2017) in the context of a latent factor model featuring one global factor. They find that exploiting the informational content of the common factor improves the accuracy of growth forecasts across a large panel of countries.

Our empirical setting is different for two reasons. First, it features a lagged dependent

Table 7: Further robustness checks

	All countries			
	Spatial error		Two factors	
	Trade	Distance	Trade	Distance
g_{t-1}	0.326	0.328	0.337	0.329
	(24.828)	(24.893)	(25.454)	(24.794)
Wg_t	0.089	-0.238	0.365	0.128
	(0.173)	(-2.645)	(12.735)	(6.015)
Wg_{t-1}	0.089	0.139	-0.103	0.016
	(0.173)	(3.495)	(-2.237)	(0.613)
Spatial error	0.513	0.327		
	(0.336)	(4.106)		
Pesaran CD statistic	1.806	3.847	-0.511	-0.245
(p-value)	(0.035)	(0.000)	(0.305)	(0.403)
Exponent of CSD	0.684	0.703	0.433	0.525
R^2	0.227	0.246	0.308	0.307
$\bar{R}^2$	0.201	0.221	0.262	0.261
	Advanced countries			
	Spatial error		Two factors	
	Trade	Distance	Trade	Distance
g_{t-1}	0.439	0.380	0.435	0.402
	(14.197)	(11.217)	(14.539)	(12.815)
Wg_t	-0.143	0.196	0.766	0.261
	(-0.159)	(0.237)	(39.099)	(5.453)
Wg_{t-1}	0.021	-0.230	-0.243	-0.029
	(0.057)	(-0.918)	(-6.534)	(-0.445)
Spatial error	0.866	0.006		
	(1.059)	(0.008)		
Pesaran CD statistic	-1.865	-1.14	1.665	-3.292
(p-value)	(0.031)	(0.127)	(0.048)	(0.000)
Exponent of CSD	0.527	0.430	0.615	0.536
R^2	0.610	0.520	0.699	0.638
$\bar{R}^2$	0.580	0.483	0.648	0.578

Notes: GDP growth is the first difference of the log of real GDP. 'Pesaran CD statistic' is the cross-sectional dependence statistic of Pesaran (2015). 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). T-statistics in brackets. The sample period covers 1970-2016.

variable. Second, it includes spatial effects in addition to a common factor. To assess the forecasting performance of our model, and in particular the respective contributions of the spatial effects and the common factor, we divide the sample into an estimation period from 1970 to 2013 and a forecasting period from 2014 to 2016. We estimate the model over the former period under both the distance and trade matrices, in the latter case using a re-computed trade weight matrix covering the years 1970 to 2013. We do this for the full model as well as the reduced models of Table 6 that exclude the common factors and/or the spatial effects – a total of four model versions under each weight matrix and country sample. Finally, for each of the model versions featuring a common factor, we fit an autoregressive model to the estimated factor; in every case, an $AR(1)$ process proved sufficient.

Equipped with these estimates, we compute out-of-sample dynamic forecasts up to 3 years ahead. The results are reported in Table 8. The prediction performance is measured by the root mean square error (RMSE). The upper panel reports results for the full sample and the lower panel reports the results for the advanced country sample.

Several facts stand out. First, neglecting cross-sectional dependence altogether – by omitting both spatial effects and common factors – results in abysmal forecasting performance in all cases. Second, in both samples and at all horizons the best forecasts result from a model including both common factors and spatial effects – with the latter based on the trade weight matrix in the full sample, and the distance matrix in the advanced-country sample.[20] Third, the factor-only model is a close second: in both samples, it outperforms the spatial-only models, by a margin that is especially large in the advanced-country sample.

[20] In the advanced-country sample, Table 8 shows that the forecasting performance of the factor-and-spatial model is much worse when using the trade weight matrix than when using the distance weight matrix. The reason is that the estimated common factor exhibits much less persistence under the former specification, and therefore it is of much less help in forecasting future growth.

Table 8: Out-of-sample dynamic forecast performance (RMSE, percent)

	All countries		
Forecast horizon	1 year	2 years	3 years
CSD specification			
None	2.870	4.603	3.724
Factor only	2.122	3.889	3.280
Spatial only: trade weight matrix	2.308	4.146	3.332
Spatial only: distance weight matrix	2.340	4.216	3.364
Factor and spatial: trade weight matrix	2.080	3.869	3.248
Factor and spatial: distance weight matrix	2.133	3.905	3.311
	Advanced countries		
	1 year	2 years	3 years
None	2.077	5.139	1.951
Factor only	1.528	4.535	0.971
Spatial only: trade weight matrix	1.927	5.038	1.660
Spatial only: distance weight matrix	1.926	5.048	1.690
Factor and spatial: trade weight matrix	1.930	5.014	1.605
Factor and spatial: distance weight matrix	1.465	4.437	0.951

Notes: The table shows the RMSE of dynamic forecasts over 2014-2016 obtained with model estimates using data for 1970-2013 under alternative specifications of cross-sectional dependence. Specifications including a common factor use an AR(1) model to predict its future values.

5 Conclusion

Output growth displays substantial comovement across countries. Existing empirical literature has modeled the cross-sectional dependence of growth as reflecting either localized linkages across countries or regions, or pervasive common shocks – i.e., weak and strong cross-sectional dependence, respectively. In this paper we have brought both perspectives together by assessing the international comovement of GDP growth in a setting that allows for both spatial dependence and latent common factors, using annual GDP growth data over the years 1970–2016 for 117 advanced and developing countries.

In the paper's empirical setting, the dynamics of growth reflect the action of global common factors as well as spatial effects accruing through the growth of economically neighboring countries. Estimation employs a bias-corrected quasi-maximum likelihood procedure recently developed by Shi and Lee (2017), alternatively considering all 117 sample countries, or a subsample of 21 advanced economies. To capture the interactions among countries, we employ two alternative spatial weight matrices – one based on bilateral trade, and another based on geographic distance. To determine the number of latent common factors driving GDP growth across the world, we use a variety of information criteria. On the whole, they indicate the presence of a single factor for both country samples considered.

Under the two alternative specifications of the spatial weight matrix, growth across the world reflects the action of global shocks, as captured by a latent common factor which, as in Kose, Otrok and Whiteman (2003), we interpret as summarizing the 'global business cycle'. Also, growth displays significant inertia. In addition, there is strong evidence of spatial effects across countries, although their magnitude is consistently larger under the trade weight matrix than under the spatial weight matrix. The implication is that both global shocks and local interactions are important to understand the cross-country comovement of output growth.

In turn, the estimated common factor is strongly positively correlated with worldwide TFP growth, in line with the predictions of the standard real business cycle model.

Despite its simplicity, the empirical model does a good job at accounting for observed growth patterns: it accounts for over 50 percent of the variation of GDP growth in the advanced-country subsample, and over 20 percent in the full country sample.

Our results also shed light on the determinants of countries' exposure to global shocks, an issue at the core of the policy debate. We find that the impact of the common factor on real output growth is bigger in countries that exhibit higher trade openness and a larger degree of specialization on commodities. In contrast, the impact is smaller in countries featuring greater financial depth.

Our results also illustrate the consequences of improperly ignoring cross-sectional dependence when analyzing growth patterns across the world. Omitting both common factors and spatial effects from the empirical model causes major distortions in the parameter estimates, leading in particular to a gross overstatement of the persistence of growth. It also results in a sharp deterioration of the model's explanatory power, as well as its out-of-sample forecasting performance. Adding either common factors or spatial effects, but not both, helps ameliorate these problems, but does not fully solve them.

In summary, the paper's encompassing specification including common factors along with spatial effects offers the best performance in terms of both in-sample fit and out-of-sample forecasts. Overall, these results confirm the need to account for cross-sectional dependence, both strong and weak, in empirical modeling of growth across countries.

References

Anderson, J. and E. van Wincoop., (2004) "Trade Costs." *Journal of Economic Literature*, 42, 691–751.

Anselin, L. (1988). "Spatial Econometrics: Methods and Models." *Kluwer Academic Publishers.*

Bai, J., and Li, K. (2018) " Dynamic spatial panel data models with common shocks." *Unpublished manuscript.*

Bailey, N., Holly, S., Pesaran, M.H., (2016) " A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence." *Journal of Applied Econometrics*, 31, 249–280.

Bailey, N., Kapetanios, and Pesaran, M.H. (2015) "Exponent of Cross-Sectional Dependence: Estimation and Inference." *Journal of Applied Econometrics*, 31, 929–960.

Baker, S.R., Bloom, N. and Davis, S.J., 2016. (2016) "Measuring economic policy uncertainty." *The Quarterly Journal of Economics*, 131, 1593-1636.

Baker, S.R. and Bloom, N., 2013. (2013) " Does uncertainty reduce growth? Using disasters as natural experiments." *National Bureau of Economic Research Working Paper* 19475.

Baltagi, B.H. and Li, Q., 1996. (1996) "Testing AR(1) against MA(1) disturbances in an error component model." *Journal of Econometrics*, 68, 133-151.

Barrot, D., C. Calderón and L. Servén. (2018) "Openness, specialization, and the external vulnerability of developing countries." *Journal of Development Economics*, 134, 310–328.

Bjornland, H., Ravazzolo, F., and Thorsrud, L.A. (2017) “Forecasting GDP with global components: this time is different.” *International Journal of Forecasting*, 33, 153–173.

Choi, I., and H. Jeong (2018) “Model selection for factor analysis: Some new criteria and performance comparisons.” *Econometric Reviews*, 1-20.

Chudik A., and Pesaran, M.H. (2016). “Theory and practice of GVAR modeling.” *Journal of Economic Surveys*, 30, 165–197.

Crucini, M.J., Kose, M.A. and Otrok, C., (2011) “What are the driving forces of international business cycles?” *Review of Economic Dynamics*, 14, 156-175.

Ductor, L., and Leiva-Leon, D. (2016). “Dynamics of global business interdependence.” *Journal of International Economcs*,102, 110-127.

Elhorst, P., (2014) *Spatial Econometrics: From Cross-sectional Data to Spatial Panels. Springer, Berlin.*

Ertur, C., and Koch, W. (2007). “Growth, technological interdependence and spatial externalities: theory and evidence.” *Journal of applied econometrics*, 22, 1033-1062.

Ertur, C., and Koch, W. (2011). “A contribution to the theory and empirics of Schumpeterian growth with worldwide interactions.” *Journal of Economic Growth*, 16, 215-255.

Ertur, C., and Musolesi, A. (2017). “Weak and strong cross-sectional dependence a panel data analysis of international technology diffusion.” *Journal of Applied Econometrics*, 32, 477–503.

Frankel, J. A. and Rose, A. K. (1998) “The endogeneity of the optimum currency area criteria.” *Economic Journal*,108, 1009–1025.

Hevia, C. and ServÃĺn, L. (2018) “Assessing the degree of international consumption risk-sharing.” *Journal of Development Economics*, 134, 176-190.

Ho, C.Y., Wang, W. and Yu, J. (2013). "Growth spillover through trade: A spatial dynamic panel data approach." *Economics Letters*, 120, 450-453.

Jorg, B. and Sandra, E., (2016) "Analyzing International Business and Financial Cycles using Multi-Level Factor Models: A Comparison of Alternative Approaches." *In Dynamic Factor Models (pp. 177-214). Emerald Group Publishing Limited.*

Karadimitropoulou, A., and Leon-Ledesma, M. (2013). "World, country, and sector factors in international business cycles." *Journal of Economic Dynamics and Control*, 37, 2913–2927.

Kose, M.A., Otrok, C. and Prasad, E. (2012) "Global business cycles: convergence or decoupling?" *International Economic Review*, 2, 511-538.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman (2003). "International Business Cycles: World, Region and Country Specific Factors." *American Economic Review*, 4, 1216-1239.

Kose, M. Ayhan, Yi, K.M., (2006). "Can the standard international business cycle model explain the relation between trade and comovement?" *Journal of international Economics*, 2, 267-295.

Kose, M.M.A., Terrones, M.M. and Prasad, M.E., (2004) "Volatility and comovement in a globalized world economy: An empirical exploration." *in Macroeconomic Policies in the World Economy, ed. by Horst Siebert*, Berlin, Springer-Verlag.

Kuersteiner, G. and I.R. Prucha (2018). "Dynamic Spatial Panel Models: Networks, Common Shocks, and Sequential Exogeneity." *Unpublished manuscript.*

Leamer, E. (1984). "Sources of International Comparative Advantage: Theory and Evidence." *Cambridge, MA: MIT Press.*

Leamer, E. (1995). "The Heckscher-Ohlin Model in Theory and Practice." *Princeton Studies in International Finance.*

LeSage, J. and Pace, R. (2009). *Introduction to Spatial Econometrics. Boca Raton: Taylor and Francis.*

Moench, E., Ng, S. and Potter, S. (2013). "Dynamic hierarchical factor models." *Review of Economics and Statistics*, 5, 1811-1817.

Mumtaz, H., Simonelli, S., and Surico, P. (2011). "International comovements, business cycle and inflation: a historical perspective." *Review of Economic Dynamics*, 14, 176–198.

Onatski, A. (2012). "Asymptotics of the principal components estimator of large factor models with weakly influential factors." *Journal of Econometrics*, 168, 244–258.

Pesaran, M. H., Schuermann, T., and Weiner, S. (2004). "Modeling regional interdependencies using a global error-correcting macroeconomic model." *Journal of Business and Economic Statistics*, 22, 129–162.

Pesaran, M. H. and E. Tosetti (2011). "Large panels with common factors and spatial correlation." *Journal of Econometrics*, 161, 182–202.

Pesaran, M. H. (2015). "Testing weak cross-sectional dependence in large panels." *Econometric Reviews*, 34, 1089–1117.

Shi, W., and Lee, L.F. (2017). "Spatial dynamic panel data models with interactive fixed effects." *Journal of Econometrics*, 197, 323–347.

Tao, J. and Yu, J. (2012). "The spatial time lag in panel data models." *Economics Letters*, 117, 544–547.

Vega, S.H. and Elhorst, J.P. (2016). " A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors." *Regional Science and Urban Economics*, 60, pp.85-95.

Wang, M., Wong, M., and Granato, J. (2015). "International comovement of economic fluctuations: a spatial analysis." *World Development*, 67, 186–201.

World Trade Organization (2018). *World Trade Statistical Review 2018. WTO, Geneva.*

Appendix A: Additional tables

Table A1: List of countries

All countries							Advanced countries	
	Country	ISO Code		Country	ISO code		Country	ISO Code
1	Albania	ALB	61	Lesotho	LSO	1	Australia	AUS
2	Algeria	DZA	62	Madagascar	MDG	2	Austria	AUT
3	Angola	AGO	63	Malawi	MWI	3	Belgium	BEL
4	Argentina	ARG	64	Malaysia	MYS	4	Canada	CAN
5	Australia	AUS	65	Mali	MLI	5	Denmark	DNK
6	Austria	AUT	66	Mauritania	MRT	6	Finland	FIN
7	Bahrain	BHR	67	Mauritius	MUS	7	France	FRA
8	Bangladesh	BGD	68	Mexico	MEX	8	Germany	DEU
9	Belgium	BEL	69	Mongolia	MNG	9	Greece	GRC
10	Benin	BEN	70	Morocco	MAR	10	Ireland	IRL
11	Bhutan	BTN	71	Mozambique	MOZ	11	Italy	ITA
12	Bolivia	BOL	72	Myanmar	MMR	12	Japan	JPN
13	Botswana	BWA	73	Namibia	NAM	13	Netherlands	NLD
14	Brazil	BRA	74	Nepal	NPL	14	New Zealand	NZL
15	Bulgaria	BGR	75	Netherlands	NLD	15	Norway	NOR
16	Burkina Faso	BFA	76	New Zealand	NZL	16	Portugal	PRT
17	Burundi	BDI	77	Nicaragua	NIC	17	Spain	ESP
18	Cambodia	KHM	78	Niger	NER	18	Sweden	SWE
19	Cameroon	CMR	79	Nigeria	NGA	19	Switzerland	CHE
20	Canada	CAN	80	Norway	NOR	20	United Kingdom	GBR
21	Chad	TCD	81	Oman	OMN	21	United States	USA
22	Chile	CHL	82	Pakistan	PAK			
23	China	CHN	83	Panama	PAN			
24	Colombia	COL	84	Paraguay	PAR			
25	Comoros	COM	85	Peru	PER			
26	Costa Rica	CRI	86	Philippines	PHL			
27	Cyprus	CYP	87	Poland	POL			
28	Cote d'Ivoire	CIV	88	Portugal	PRT			
29	Congo, Dem. Rep	COG	89	Qatar	QAT			
30	Denmark	DNK	90	Repblic of Korea	KOR			
31	Djibouti	DJI	91	Romania	ROM			
32	Dominican Republic	DOM	92	Saudi Arabia	SAU			
33	Ecuador	ECU	93	Senegal	SEN			
34	Egypt	EGY	94	Sierra Leone	SLE			
35	El Salvador	SLV	95	Singapore	SGP			
36	Ethiopia	ETH	96	South Africa	ZAF			
37	Fiji	FJI	97	Spain	ESP			
38	Finland	FIN	98	Sri Lanka	LKA			
39	France	FRA	99	Sudan	SDN			
40	Germany	DEU	100	Swaziland	SWZ			
41	Ghana	GHA	101	Sweden	SWE			
42	Greece	GRC	102	Switzerland	CHE			
43	Guatemala	GTM	103	Syria	SYR			
44	Guinea	GIN	104	Thailand	THA			
45	Guinea Bissau	GNB	105	Togo	TGO			
46	Haiti	HTI	106	Trinidad and Tobago	TTO			
47	Honduras	HND	107	Tunisia	TUN			
48	Hong Kong	HKG	108	Turkey	TUR			
49	Hungary	HUN	109	Uganda	UGA			
50	India	IND	110	United Arab Emirates	ARE			
51	Indonesia	IDN	111	United Kingdom	GBR			
52	Iran	IRN	112	United Republic, Tanzania	TZA			
53	Ireland	IRL	113	United States	USA			
54	Isreal	ISR	114	Uruguay	URY			
55	Italy	ITA	115	Venezuela	VEN			
56	Jamaica	JAM	116	Viet Nam	VNM			
57	Japan	JPN	117	Zambia	ZAM			
58	Jordan	JOR						
59	Kenya	KEN						
60	Lao PDR	LAO						

Table A2: Data sources and definition

Variable	Definition	Source
GDP growth	First difference of log real GDP	United Nations National Accounts
Bilateral Trade	Bilateral trade flow	IMF DOT
Total factor productivity	Computed from Solow residual using labor and capital inputs	PWT
Trade openness	Sum of total exports and imports (% of GDP)	World Bank WDI
Commodity intensity	Net Exports of Commodities (% of GDP)	UN/COMTRADE
Financial depth	Domestic credit to private sector (% of GDP)	World Bank WDI
Capital account openness	Chin-Ito Index of Capital account Liberalization	http://web.pdx.edu/ ito
Short-term real interest rate	U.S. short-term real interest rate	FRED
Uncertainty	U.S. economic policy uncertainty index	Baker, Bloom and Davis (2016)
Public sector size	Government consumption (% of GDP)	World Bank WDI
Population	Average population in millions	World Bank WDI
Commodity price	Nonfood commodity prices in real terms	World Bank

Table A3: Correlation between actual and fitted values: All countries, trade and distance weight matrices

Country	**Trade**	**Distance**	**Country**	**Trade**	**Distance**
Albania	0.385	0.403	Malawi	0.000	-0.039
Algeria	0.123	0.102	Malaysia	0.579	0.555
Angola	0.491	0.521	Mali	0.219	0.140
Argentina	0.286	0.332	Mauritania	0.088	0.115
Australia	0.241	0.185	Mauritius	0.320	0.345
Austria	0.647	0.481	Mexico	0.441	0.333
Bahrain	0.445	0.334	Mongolia	0.673	0.661
Bangladesh	0.291	0.357	Morocco	-0.382	-0.422
Belgium	0.672	0.601	Mozambique	0.476	0.401
Benin	-0.080	-0.028	Myanmar	0.620	0.570
Bhutan	0.305	0.345	Namibia	0.409	0.338
Bolivia	0.638	0.695	Nepal	-0.115	-0.070
Botswana	0.508	0.568	Netherlands	0.761	0.590
Brazil	0.610	0.618	New Zealand	0.361	0.362
Bulgaria	0.636	0.634	Nicaragua	0.273	0.297
Burkina Faso	0.087	-0.023	Niger	0.046	0.053
Burundi	0.215	0.197	Nigeria	0.445	0.448
Cambodia	0.588	0.581	Norway	0.648	0.588
Cameroon	0.520	0.518	Oman	0.218	0.166
Canada	0.770	0.679	Pakistan	0.161	0.202
Chad	0.271	0.281	Panama	0.345	0.364
Chile	0.479	0.521	Paraguay	0.454	0.468
China	0.003	0.077	Peru	0.524	0.527
Colombia	0.668	0.691	Philippines	0.627	0.624
Comoros	-0.027	0.056	Poland	0.627	0.637
Costa Rica	0.608	0.571	Portugal	0.710	0.584
Cyprus	0.456	0.459	Qatar	0.529	0.520
Cote d'Ivoire	0.367	0.360	Repblic of Korea	0.393	0.396
Congo, Dem. Rep.	0.750	0.771	Romania	0.782	0.797
Denmark	0.584	0.469	Saudi Arabia	0.402	0.441
Djibouti	0.080	0.123	Senegal	-0.096	-0.161
Dominican Republic	0.438	0.447	Sierra Leone	0.495	0.496
Ecuador	0.464	0.489	Singapore	0.593	0.594
Egypt	0.272	0.303	South Africa	0.614	0.631
El Salvador	0.760	0.728	Spain	0.832	0.753
Ethiopia	0.393	0.387	Sri Lanka	0.362	0.310
Fiji	-0.031	-0.031	Sudan	0.213	0.221
Finland	0.718	0.681	Swaziland	0.461	0.425
France	0.808	0.733	Sweden	0.590	0.506
Germany	0.656	0.582	Switzerland	0.615	0.539
Ghana	0.472	0.477	Syria	0.320	0.325
Greece	0.585	0.559	Thailand	0.575	0.550
Guatemala	0.847	0.870	Togo	0.213	0.205
Guinea	0.109	0.089	Trinidad Tobago	0.712	0.705
Guinea Bissau	-0.189	-0.146	Tunisia	0.266	0.243
Haiti	0.095	0.148	Turkey	0.331	0.307
Honduras	0.583	0.548	United Republic, Tanzania	0.559	0.526
Hong Kong	0.556	0.646	Uganda	0.554	0.512
Hungary	0.657	0.667	United Arab Emirates	0.371	0.430
India	0.031	0.081	United Kingdom	0.565	0.493
Indonesia	0.510	0.468	United States	0.617	0.599
Iran	0.371	0.378	Uruguay	0.608	0.647
Ireland	0.442	0.442	Venezuela	0.404	0.426
Isreal	0.420	0.426	Viet Nam	0.323	0.318
Italy	0.748	0.642	Zambia	0.400	0.391
Jamaica	0.419	0.324	**Median**	**0.460**	**0.463**
Japan	0.640	0.568			
Jordan	0.541	0.544			
Kenya	0.482	0.492			
Lao PDR	0.079	0.036			
Lesotho	0.354	0.347			
Madagascar	-0.032	-0.146			

Table A4: Correlation between actual and fitted values: Advanced countries, trade and distance weight matrices

Country	Trade	Distance
Australia	0.302	0.327
Austria	0.758	0.667
Belgium	0.743	0.738
Canada	0.842	0.779
Denmark	0.725	0.705
Finland	0.794	0.849
France	0.899	0.858
Germany	0.789	0.803
Greece	0.599	0.637
Ireland	0.995	0.622
Italy	0.855	0.837
Japan	0.671	0.716
Netherlands	0.850	0.809
New Zealand	0.323	0.335
Norway	0.652	0.658
Portugal	0.808	0.799
Spain	0.893	0.871
Sweden	0.725	0.778
Switzerland	0.652	0.641
United Kingdom	0.688	0.721
United States	0.776	0.812
Median	**0.758**	**0.738**

Credit author statement

Luis Servén: research design, methodology, writing, reviewing, validating, overall supervision. ***Girum Abate:*** empirical design, methodology, econometric analysis, drafting, reviewing.