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# Adding Space to the International Business Cycle

*Girum Dagnachew Abate*
*Luis Servén*

WORLD BANK GROUP
Development Economics
Development Research Group
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## 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 rises with their openness to trade and the degree of commodity specialization of their economies. Despite its simplicity, the empirical model fits the data well, especially for advanced countries. 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.


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Girum Dagnachew Abate and Luis Servén*

The World Bank Group

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*Email addresses: gabate@worldbank.org, lserven@worldbank.org. We are indebted to Paul Elhorst for helpful comments. 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.

# 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 regional (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 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)).

[1]Strong and weak cross-sectional dependence can be 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).

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 depend on its precise form. If spatial dependence accrues through the 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 produce 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 more than 100 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 hence 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 positive contemporaneous spatial lag and a negative spatial-time lag, with both statistically significant in virtually all specifications, implying 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 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.

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.

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 dramatically 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 address the cross-sectional dependence. Including both the factor and the spatial effect 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 (SDPD) 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 $V_t$.

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 $\rho$ and the space-time lag coefficient $\lambda$.[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 $\Psi$ measures the (possibly heterogeneous) effect of the factors on each country's growth. Finally, growth persistence is captured by the parameter $\beta$ 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 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).[3]

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

[2]The parameter $\lambda$, termed 'diffusion parameter' by Shi and Lee (2017), captures spatio-temporal correlations in output growth that may result from partial adjustment or inter-temporal decision making by economic agents, see e.g., Tao and Yu (2012).

[3]Equation (1) can also be seen as a variant of the GVAR model of Chudik and Pesaran (2016) imposing constant $\beta, \lambda$ and $\rho$ across. In turn, the common factor framework in (1) encompasses individual and time period fixed effects as a particular case (Shi and Lee (2017)). To see this, consider the specification

$$g_t = \rho\, W g_t + \beta g_{t-1} + \lambda\, W g_{t-1} + \zeta + \iota \xi_t + \varepsilon_t,$$

where $\zeta = (\zeta_1 \;\; \zeta_2 \;\; \cdot \;\; \cdot \;\; \zeta)'$ are individual effects, and $\xi_t$ are time effects with $\iota = (1 \;\; 1 \;\; \cdot \;\; \cdot \;\; 1)'$, where

$$\Psi_n = \begin{pmatrix} \zeta_1 & \zeta_2 & \cdot & \cdot & \zeta \\ 1 & 1 & \cdot & \cdot & 1 \end{pmatrix} \text{ and } F_T = \begin{pmatrix} 1 & 1 & \cdot & \cdot & 1 \\ \xi_1 & \xi_2 & \cdot & \cdot & \xi \end{pmatrix}.$$

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 $g_t = Ag_{t-1} + S^{-1}(\Psi f_t + V_t)$. 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 $\omega_{min}$ is the smallest characteristic root of the weight matrix $W$, see Shi and Lee (2017).[4]

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.

## 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. In their case, however, the spatial effects accrue through the error term, while here they accrue through the dependent variable. This implies that the two-stage estimation approach is not applicable in our setting. 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.

In settings more similar to ours, Kuersteiner and Prucha (2015) propose a GMM-type estimator, while Bai and Li (2015) develop a quasi-maximum likelihood (QML) estimator. In this paper, we employ the QML estimation approach recently developed by Shi and Lee (2017). We provide a brief outline next, 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 $\delta = (\lambda)'$, $\sigma^2$, $\Psi$ and $F_T$. Then the quasi-log likelihood function of the model in equation (1) is

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

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

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

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

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 $\eta$ as the parameter of interest, and concentrating out the factors and their loadings applying principal component analysis, the concentrated log-likelihood is

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

where $G(\eta) = \frac{1}{nT} \sum_{i=r+1}^{n} \mu_i (S - \sum_{k=1}^{K} Z_k\delta_k)(S - \sum_{k=1}^{K} Z_k\delta_k)'$. The QML estimator is derived from the optimization problem in equation (5). The estimate of the factor loadings $\Psi$ is computed from the eigenvectors associated with the first $r$ largest eigenvalues of $(S - \sum_{k=1}^{K} Z_k\delta_k)(S - \sum_{k=1}^{K} Z_k\delta_k)'$. 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 may be asymptotically biased owing to an incidental parameters problem that arises from the presence of predetermined regressors (the lagged dependent variable) as well as the interaction between the spatial effects and the factor loadings. To tackle this issue, Shi and Lee (2017) develop a bias correction that yields an asymptotically normal, properly-centered estimator.[5] The estimations reported below for the specifications including common factors employ the bias-corrected estimator; Appendix B provides a brief description of the correction.

# 3 Data

We use a large cross-country data set drawn from the United Nations National Accounts database. 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.[6] The sample countries account for more than 90% of world GDP in 2016.

[5] Vega and Elhorst (2016) also employ QML estimation in a setting featuring both spatial effects and common factors, specifying the latter as cross-sectional averages as in Pesaran and Tosetti (2011), and assuming that each cross-sectional unit is too small to affect the averages, so that they can be assumed exogenous – an assumption unlikely to hold in our setting as the sample includes some very large economies.

[6] We employ GDP growth data from the United Nations National Accounts database because it reaches up to 2016. In contrast, PWT 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.

Because advanced countries feature higher trade and financial integration (see Kose, Terrones and Prasad (2004)) than other countries, 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.

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 $i$ and $j$, $i \neq j$, 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.[7]

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 $j$.[8]

To assess the covariates of the common factors, we consider three candidate variables, namely, (i) total factor productivity; (ii) policy uncertainty, and (iii) the U.S. short-term real interest rate. 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.

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

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

[8]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.

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.

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); (v) the degree of flexibility of the exchange rate regime, summarized by the index of de facto exchange rate arrangements of Ghosh, Ostry, Kapan and Qureshi (2015); (vi) the size of the public sector measured as government consumption as a percentage of GDP; and (vii) the size of the economy, as captured by total population.

Figure 1: Average real output growth

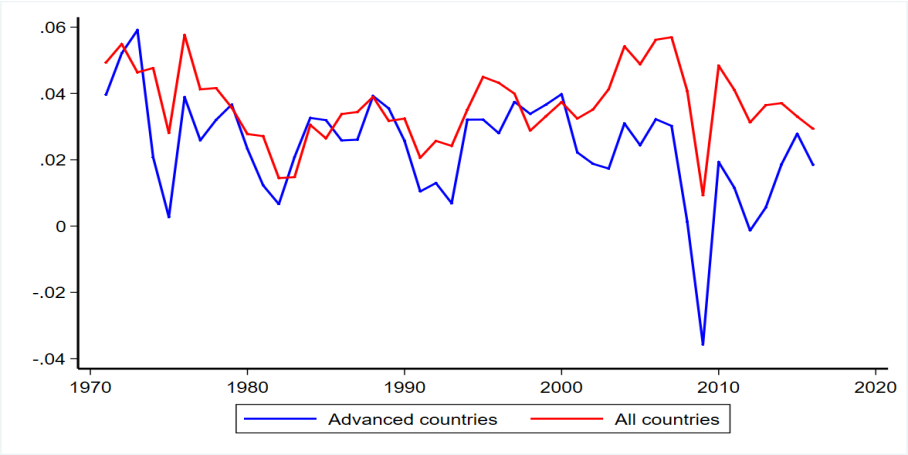



Figure 1 depicts the time path of average real GDP growth for both the full and advanced country samples. The trends are similar in both cases, although growth is consistently higher in the former (3.6% on average over the entire sample period) than in the latter (2.3%). The figure also shows major recessions 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 countries (see also Kose, Otrok and Prasad (2012)).

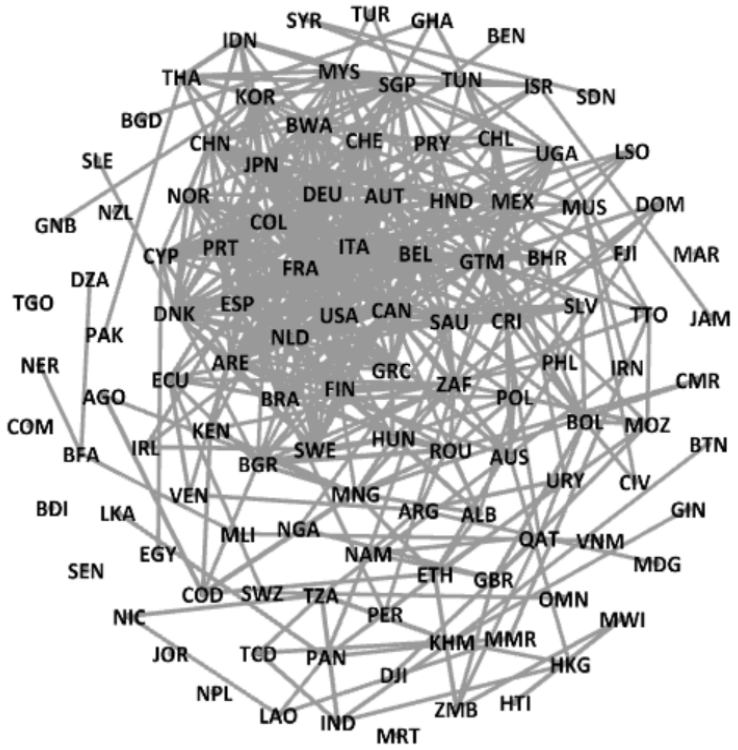
## 4 Empirical results

As a first step, we compute the pairwise correlation of real output growth across countries, and visualize it using network maps.[9] Figure 2 shows the network map of pairwise growth correlations for the full sample. The average and median correlations are, respectively, 0.103 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

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

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, Germany, Italy, Spain, the Netherlands, USA and Colombia, among others. African countries such as Togo, the Comoros and Burundi exhibit relatively low connection in the system.

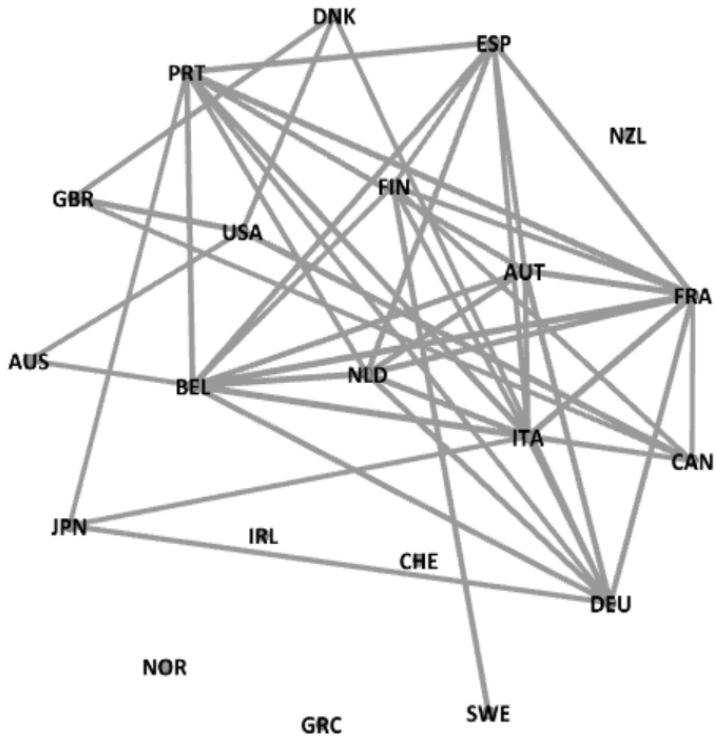
Figure 2: Real GDP growth correlation, all countries




Notes: The pairwise correlation between two countries is indicated by the connecting line. Pairwise correlations less than 0.4 are dropped. If two countries are not connected, it indicates the 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 correlations are, respectively, 0.478 and 0.476. 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, most of the advanced countries are connected with at least one 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.

Figure 3: Real GDP growth correlation, advanced countries




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

While the pairwise correlations indicated 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 of weak cross-sectional dependence, $CD \xrightarrow{d} N(0,1)$ for $N \to \infty$ and large $T$; see Pesaran (2015).

The second statistic is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015), defined by the standard deviation of the cross-sectional average of the observations. Specifically, the exponent $\alpha$ is given by $Std.(\tilde{x}_t) = O(N^{\alpha-1})$, where $\tilde{x}_t$ is a simple cross-sectional average of observations $x_{it}, i = 1, ...n; t = 1, ..., T$ defined by $\tilde{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$. $\alpha$ takes a value between 0 and 1. A value of 1 indicates strong cross-sectional dependence, of the type usually captured with (strong) factor models.[10]

Table 1 reports the Pesaran CD test statistic and the exponent of cross-sectional

[10]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).

dependence of real GDP growth, for the full sample (left panel) and the advanced-country sample (right panel). The CD test statistic is above 40 for both samples, overwhelmingly rejecting the null. Table 1 also reports the exponent of cross-sectional dependence $\alpha$ along with 95% confidence bands, for both the advanced and full country samples. The estimated value of $\alpha$ is 1 in the advanced-country sample (with a confidence region reaching well above 1) and .94 in the full sample. In both cases, the results 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 | 42.343 | 41.661 |
| Exponent of CSD | 0.943 | 1.004 |
| | (0.906, 0.979) | (0.905, 1.102) |
| Number of countries | 117 | 21 |

Notes: GDP growth is the first difference of the log of real GDP. 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015), and values in parenthesis are its 95% confidence bands. The sample period is 1970-2016.

## 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.[11] 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 $HQ$ suggest one factor while the $IC$ criterion suggests two factors (by a very narrow margin). We opt for employing one factor in all the estimations below.[12]

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

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

Table 2: Model selection criteria

| Criteria | All countries | | | | |
|---|---|---|---|---|---|
| | Number of factors | | | | |
| | 0 | 1 | 2 | 3 | 4 |
| IC2 | 0.000 | **-0.054** | -0.018 | 0.029 | 0.076 |
| BIC | **1.003** | 1.491 | 2.450 | 3.469 | 4.489 |
| HQ | 0.503 | **0.299** | 0.566 | 0.892 | 1.221 |
| | Advanced countries | | | | |
| IC2 | 0.000 | -0.449 | **-0.452** | -0.439 | -0.408 |
| BIC | 0.144 | **-0.029** | 0.219 | 0.483 | 0.764 |
| HQ | 0.808 | **-2.903** | -2.399 | -1.749 | -0.921 |

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-bilateral trade and bilateral inverse distance.

Consider first the full-sample results on the first two columns of the table. The coefficient estimate of lagged output growth is positive and statistically significant across all specifications indicating a significant degree of inertia in output growth.

Table 3: Estimation results

| | All countries | | Advanced countries | |
|---|---|---|---|---|
| Weight matrix | Trade | Distance | Trade | Distance |
| $g_{t-1}$ | 0.328 | 0.326 | 0.373 | 0.376 |
| | (24.748) | (24.447) | (12.020) | (12.122) |
| $Wg_t$ | 0.286 | 0.110 | 0.422 | 0.195 |
| | (9.328) | (5.120) | (8.233) | (3.941) |
| $Wg_{t-1}$ | -0.104 | 0.035 | -0.283 | -0.262 |
| | (-2.069) | (1.307) | (-3.077) | (-3.136) |
| Pesaran CD statistic | -0.732 | -0.825 | 0.161 | -1.601 |
| (p-value) | (0.232) | (0.205) | (0.436) | (0.055) |
| Exponent of CSD | 0.402 | 0.511 | 0.766 | 0.362 |
| $R^2$ | 0.224 | 0.225 | 0.526 | 0.516 |
| $\bar{R}^2$ | 0.198 | 0.199 | 0.489 | 0.478 |

Notes: GDP growth is the first difference of the log of real GDP. 'Exponent of CSD' is the exponent of cross-sectional dependence of Bailey, Kapetanios and Pesaran (2015). 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 country tends to raise growth of countries nearby 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. Still, the parameter estimate on the spatial lag is much larger when using the trade weight matrix than when using the distance matrix. Similarly, the space-time lag is negative and statistically significant under the trade weight matrix but becomes insignificant under the distance weight matrix.

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. The exponent of cross-sectional dependence also indicates no strong cross-sectional dependence in the residuals of any of the specifications.

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 spatial effects are also of larger magnitude under the trade weight matrix than under the distance weight matrix. Further, under the latter specification the CD statistic hints at residual cross-sectional dependence – suggesting that geographic distance does a poorer job than bilateral trade at capturing spatial dependence among advanced countries.

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 samples, respectively.[14]

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 .45 for the full sample and over .70 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 and Spain exhibit correlations above 0.75 under both weight matrices, while a handful of poor countries, mostly in Sub-Saharan Africa (Benin, Burkina Faso, Guinea-Bissau, Nepal, Senegal) show negative correlations. In the advanced country sample, two-thirds

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

[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.

of the 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.

## 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:

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

Then, 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 $\rho$. It also declines over time at a rate that depends on $\lambda$, $\beta$ and $\rho$. 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]

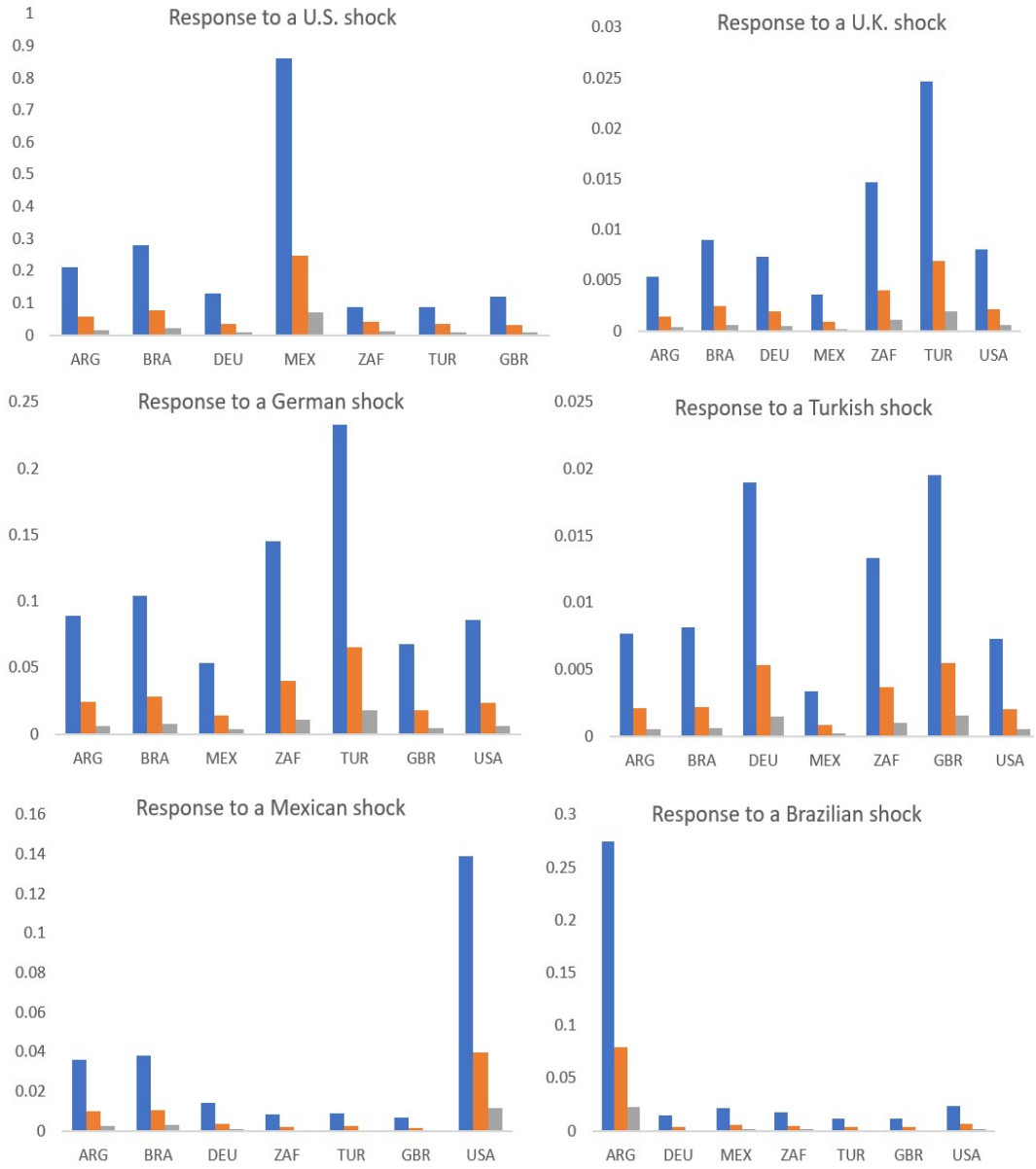
The short-run effects are, in some cases, fairly substantial. For example, a 1-percentage point shock to U.S. growth raises growth in Mexico by more than 0.8 percent. It also has sizable impacts on Brazil. Similarly, a shock to Germany raises growth in Turkey by close to a quarter point.[16]

Convergence is monotonic and quite fast – after just three years, the impacts have virtually vanished. The reason is that the eigenvalues of the transition matrix turn out to be fairly small in absolute value (under 0.4), thus implying little persistence.

[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.

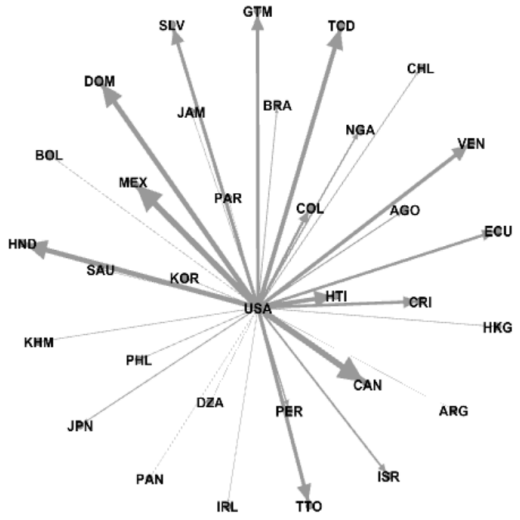
Figure 4: Dynamic spatial impacts



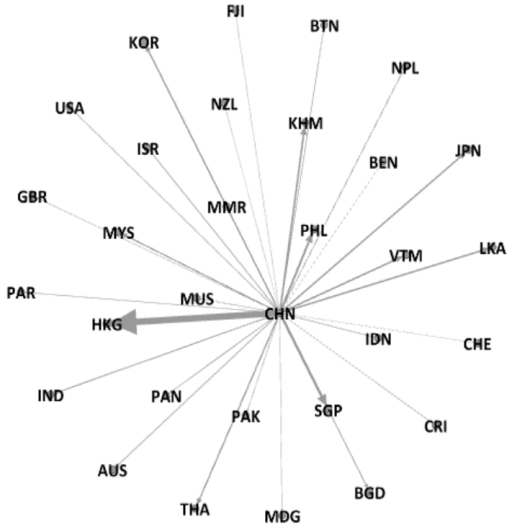

To further illustrate the propagation of output shocks, we compute the contemporaneous responses to a one-time shock to U.S., China and German output growth using the full-sample estimates under the trade specification of the weight matrix. The results are summarized in Figure 5. In the figure, the direction of the arrows indicates the transmission of shocks from the source country to the (economically) neighboring 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, Mexico, Colombia and Haiti appear to be the most affected by a U.S. output growth shock. Output growth shocks in Germany and China have their largest impacts on Austria and Hong Kong, respectively.

Figure 5: The short-run spatial transmission of shocks

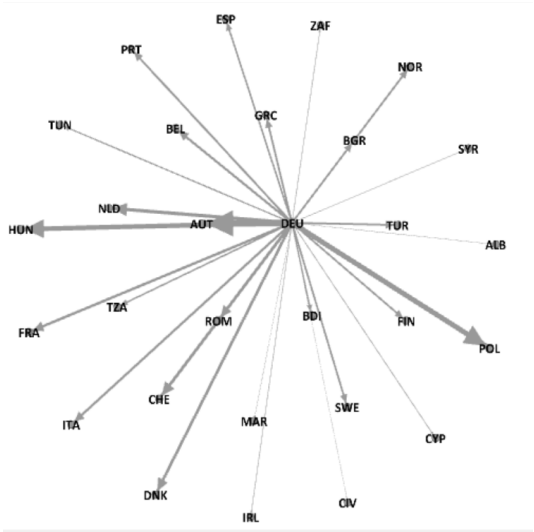
(a) US




(b) China



(c) Germany




Notes: The graph shows the short-run transmission of a one-time shock from the U.S., China 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.

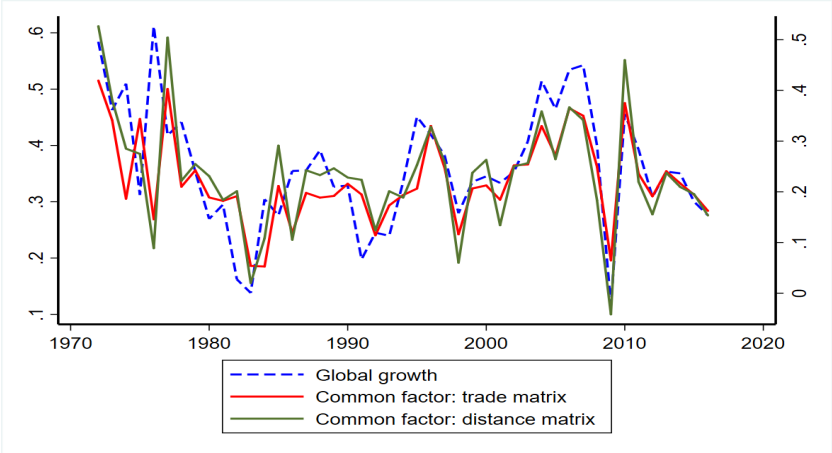
## 4.3 The common factor and the global business cycle

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 advanced-country and the full sample, along with the growth rate of world and advanced-country GDP. In both cases the common factor tracks aggregate GDP growth fairly closely. For the full country sample, the correlation of the factor with world GDP growth is .64 and .61 under the trade and distance weight matrix, respectively. For the advanced-country subsample, the correlations are .78 and .79.

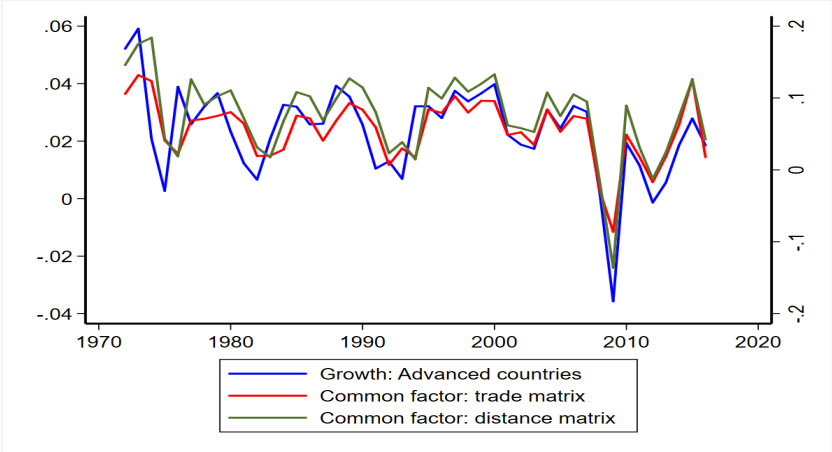
Consistent with the findings of Kose, Otrok and Whiteman (2003), the swings in the estimated factors reflect major economic episodes of the last four and a half decades – the recessions of the mid 1970s and early 1980s, the downturn of the early 1990s, and the financial crisis of 2008/09. The estimated common factors are very similar across the bilateral trade and distance matrix specifications in Table 3. For the full country sample, their pairwise correlations exceed .92; for the advanced-country sub-sample they exceed .97.

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, oil 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.

Table 4: Factor covariates, trade and distance weight matrices

| Variable | Trade weight matrix | | | |
|---|---|---|---|---|
| | I | II | III | IV |
| Δ TFP | 0.945 | | | 3.131 |
| | (2.840) | | | (1.920) |
| Uncertainty | | -0.149 | | -0.134 |
| | | (-1.840) | | (-1.600) |
| Real interest rate | | | -0.391 | -0.413 |
| | | | (-1.490) | (-1.260) |
| No. of obs. | 43 | 45 | 45 | 43 |
| $R^2$ | 0.165 | 0.078 | 0.034 | 0.343 |
| | Distance weight matrix | | | |
| Δ TFP | 5.435 | | | 4.958 |
| | (2.940) | | | (2.530) |
| Uncertainty | | -0.221 | | -0.142 |
| | | (-1.950) | | (-1.270) |
| Real interest rate | | | -0.027 | 0.127 |
| | | | (-0.070) | (0.360) |
| No. of obs. | 43 | 45 | 45 | 43 |
| $R^2$ | 0.285 | 0.134 | 0.000 | 0.345 |

Notes: The dependent variable is the common factor from the full sample estimates in Table 3. Δ TFP is the first difference of 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. 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 on total factor productivity, policy uncertainty, and the U.S. short-term interest rate, taken as a measure of global monetary conditions. 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. Next, the uncertainty index shows a negative sign with a statistically significant coefficient, showing that the adverse effect of uncertainty on output found by Baker, Bloom and Davis (2016) among major advanced countries also holds in our larger country sample. In turn, the U.S. short-term real interest rate is negatively 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 insignificant under both weight matrices. Finally, the last column of the table shows that when all three variables are considered jointly, they can account for over one-third of the variation in the common factor. However, only TFP growth remains statistically significant.

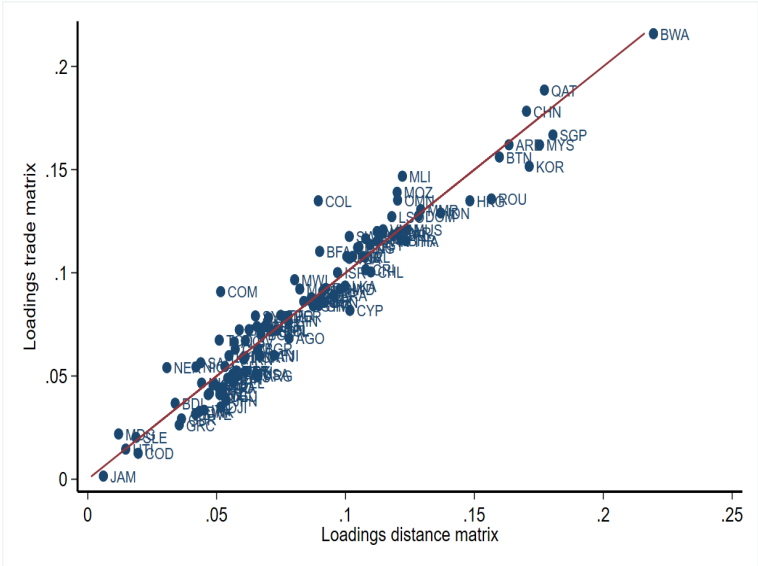
## 4.4 The exposure to the global business cycle

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.

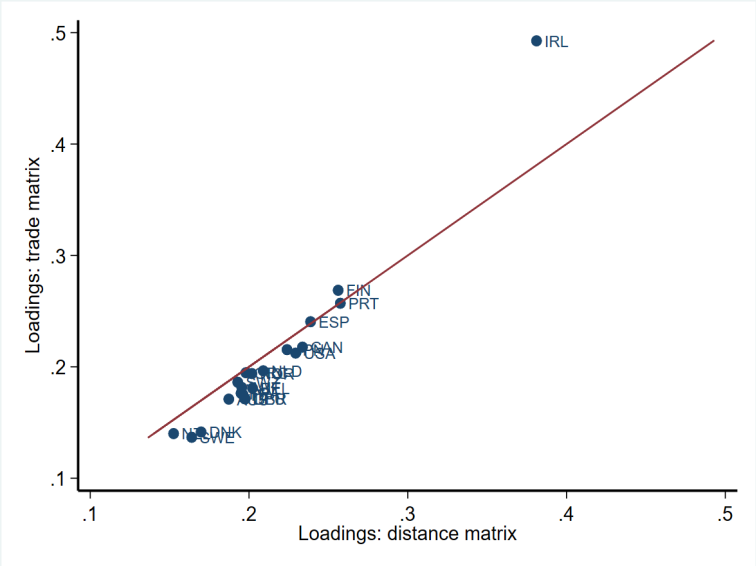
In our model, the factor loadings measure the response of each country's output growth to the common shocks. The estimated loadings (shown in Figure 7) are very similar across the two specifications in Table 3: in the full country sample, their pairwise correlations exceed .96, while for the advanced-country sample the correlation exceeds .98. The loadings are positive in all cases, indicating that the global cycle affects the growth rate of all countries in the same direction. However, the magnitude of the loadings displays considerable variation across countries. In the full sample, the largest loadings belong to Botswana, Qatar and China when using the trade-based matrix, and Botswana, Qatar and Singapore when using the distance weight matrix. In the advanced-country sample, the largest loadings correspond by far to Ireland, followed by Portugal and Finland, in both the trade-based and distance weight matrices.

Figure 7: Factor loadings

(a) All countries



(b) Advanced countries




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 financial integration. To verify this conjecture, we regress the full-sample factor loadings on selected policy and structural indicators using the full-sample results.

Specifically, the variables we consider are trade openness, capital account openness, financial depth, commodity specialization, the degree of flexibility of the exchange rate regime, the relative size of the public sector, and country size.

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. Next, a higher degree of commodity specialization should raise the economy's exposure to global cycle, to the extent that it 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.

In turn, exchange rate flexibility helps cushion external real shocks (e.g., Broda (2004)), but its ability to provide insulation from global financial disturbances remains debated. Influential work by Rey (2013) fails to find any difference across exchange rate regimes regarding their ability to shelter the economy from external (financial) shocks.[17] 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, following Redding and Venables

[17] We employ the de facto classification compiled by Ghosh, Ostry, Kapan and Qureshi (2015), which distinguishes between fixed, intermediate, and floating regimes. As used here, an increase in the value of the indicator variable denotes a more flexible regime.

(2004), we also include average population as a proxy measure of country size. In theory, a smaller country may exhibit higher growth fluctuations either because the world interest rate is less sensitive to shocks occurring in that country and/or small countries have relatively fewer firms and, thus are subject to higher growth fluctuations, see Giovanni and Levchenko (2012).

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. Hence the regressions probably understate the strength of that relationship.

Table 5: Loading covariates regression, all countries

| Variable | Trade weight matrix | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI | VII | VIII |
| Trade opnness | 0.019 | | | | | | | 0.019 |
| | (2.390) | | | | | | | (1.750) |
| Financial openness | | -0.005 | | | | | | -0.003 |
| | | (-0.97) | | | | | | ( -0.490) |
| Financial depth | | | -0.003 | | | | | -0.008 |
| | | | (-0.640) | | | | | (-1.300) |
| Commodity specialization | | | | 0.012 | | | | 0.012 |
| | | | | (4.12) | | | | (2.790) |
| Exchange rate flexibility | | | | | -0.007 | | | -0.007 |
| | | | | | (-0.81) | | | (-0.750) |
| Public sector size | | | | | | -0.0004 | | -0.001 |
| | | | | | | (-0.480) | | (-0.960) |
| Population | | | | | | | -0.0004 | 0.005 |
| | | | | | | | (-0.130) | (1.460) |
| $R^2$ | 0.061 | 0.008 | 0.004 | 0.162 | 0.005 | 0.002 | 0.000 | 0.220 |
| | Distance weight matrix | | | | | | | |
| Trade opnness | 0.022 | | | | | | | 0.020 |
| | (2.660) | | | | | | | (1.800) |
| Financial openness | | 0.001 | | | | | | 0.0002 |
| | | (0.230) | | | | | | (0.030) |
| Financial depth | | | 0.0027 | | | | | -0.005 |
| | | | (0.510) | | | | | (-0.700) |
| Commodity specialization | | | | 0.011 | | | | 0.011 |
| | | | | (3.770) | | | | (2.630) |
| Exchange rate flexibility | | | | | -0.004 | | | -0.003 |
| | | | | | (-0.500) | | | (-0.320) |
| Public sector size | | | | | | -0.0002 | | -0.001 |
| | | | | | | (-0.310) | | (-0.760) |
| Population | | | | | | | 0.0002 | 0.006 |
| | | | | | | | (0.080) | (1.580) |
| $R^2$ | 0.081 | 0.001 | 0.003 | 0.144 | 0.002 | 0.041 | 0.001 | 0.247 |

Notes: The table shows regression of the factor loadings from the full sample estimates in Table 3 on the variables shown. An increase in the value of the exchange rate regime variable denotes a more flexible regime. 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.

Table 5 reports the regression results using the factor loadings as dependent variable. The upper panel reports the results obtained from the trade weight matrix, and the bottom panel reports the results obtained using 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). This also holds true for regression results using all the variables jointly, as shown in the final column of the table. The remaining variables 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.[18]

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 show overwhelming evidence of (strong) residual dependence. In addition, the overall fit of the model, as measured by the $R^2$, is quite 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 still hint at dependence among the residuals. Finally, the fit of the model shows a considerable improvement relative to the preceding column.

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

Table 6: Robustness checks

| | All countries | | | |
|---|---|---|---|---|
| | | | Spatial only | |
| | None | Factor only | Trade | Distance |
| $g_{t-1}$ | 0.592 | 0.329 | 0.379 | 0.400 |
| | (43.024) | (24.666) | (29.583) | (31.170) |
| $Wg_t$ | | | 0.607 | 0.304 |
| | | | (31.186) | (16.023) |
| $Wg_{t-1}$ | | | 0.003 | 0.177 |
| | | | (0.124) | (8.084) |
| Pesaran CD statistic | 49.889 | -0.861 | 12.526 | 31.885 |
| (p-value) | (0.000) | (0.195) | (0.000) | (0.000) |
| Exponent of CSD | 0.910 | 0.462 | 0.670 | 0.827 |
| $R^2$ | 0.129 | 0.219 | 0.168 | 0.143 |
| $\bar{R}^2$ | 0.074 | 0.194 | 0.166 | 0.132 |
| | Advanced countries | | | |
| | | | Spatial only | |
| | None | Factor only | Trade | Distance |
| $g_{t-1}$ | 0.683 | 0.376 | 0.428 | 0.438 |
| | (16.645) | (11.983) | (14.219) | (14.418) |
| $Wg_t$ | | | 0.735 | 0.659 |
| | | | (32.452) | (26.132) |
| $Wg_{t-1}$ | | | -0.193 | -0.147 |
| | | | (-4.612) | (-3.440) |
| Pesaran CD statistic | 40.773 | 2.166 | 3.080 | 7.673 |
| (p-value) | (0.000) | (0.015) | (0.001) | (0.000) |
| Exponent of CSD | 1.004 | 0.770 | 0.683 | 0.789 |
| $R^2$ | 0.163 | 0.503 | 0.461 | 0.424 |
| $\bar{R}^2$ | 0.082 | 0.462 | 0.458 | 0.423 |

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

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 exaggerating 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. In fact, the magnitude and the significance of the spatial lag parameter appear substantially overstated relative to the results shown in

Table 3. In turn, the cross-sectional dependence statistics show in general lower values than in the first column of Table 6, but the CD statistic still shows 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 lower 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 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, where the contemporaneous spatial lag coefficient becomes negative. The rest of the estimates show little change relative to the baseline. In the advanced-country sample, the parameter estimates of the space-time lag variable are insignificant, as is that of the spatial lag under the distance weight matrix. 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 as dictated by the information criteria. The main consequence is that the spatial lag coefficient becomes larger, especially under the trade weight matrix. The spatial effects follow the same pattern as in Table 3 – the estimated coefficients are larger (in absolute value) under the trade weight matrix than under the inverse distance weight matrix. With an additional factor, the fit of the model improves relative to that in Table 3. However, in the advanced-country sample the CD statistics continue to show evidence against the null of weak cross-sectional dependence.

Table 7: Further robustness checks

| | All countries | | | |
|---|---|---|---|---|
| | Spatial error | | Two factors | |
| | Trade | Distance | Trade | Distance |
| $g_{t-1}$ | 0.328 | 0.330 | 0.334 | 0.329 |
| | (24.730) | (24.649) | (24.842) | (24.466) |
| $Wg_t$ | -0.316 | -0.211 | 0.355 | 0.114 |
| | (-0.046) | (-1.928) | (12.276) | (5.324) |
| $Wg_{t-1}$ | 0.077 | 0.144 | -0.134 | 0.024 |
| | (0.038) | (3.237) | (-2.846) | (0.919) |
| Spatial error | 0.646 | 0.305 | | |
| | (0.095) | (3.067) | | |
| Pesaran CD statstic | 1.190 | 3.203 | -0.580 | -0.577 |
| (p-value) | (0.117) | (0.001) | (0.281) | (0.282) |
| Exponent of CSD | 0.694 | 0.701 | 0.487 | 0.482 |
| $R^2$ | 0.222 | 0.240 | 0.311 | 0.305 |
| $\bar{R}^2$ | 0.197 | 0.215 | 0.260 | 0.258 |
| | Advanced countries | | | |
| | Spatial error | | Two factors | |
| | Trade | Distance | Trade | Distance |
| $g_{t-1}$ | 0.341 | 0.376 | 0.426 | 0.378 |
| | (10.884) | (11.006) | (13.983) | (11.855) |
| $Wg_t$ | 0.539 | 0.211 | 0.779 | 0.244 |
| | (2.663) | (0.294) | (42.005) | (5.051) |
| $Wg_{t-1}$ | 0.015 | -0.262 | -0.245 | -0.123 |
| | (0.096) | (-1.238) | (-6.567) | (-1.672) |
| Spatial error | 0.390 | -0.007 | | |
| | (1.428) | (-0.009) | | |
| Pesaran CD statstic | 4.060 | -1.537 | 2.391 | -3.381 |
| (p-value) | (0.000) | (0.062) | (0.008) | (0.000) |
| Exponent of CSD | 0.735 | 0.370 | 0.638 | 0.477 |
| $R^2$ | 0.572 | 0.516 | 0.694 | 0.630 |
| $\bar{R}^2$ | 0.537 | 0.479 | 0.643 | 0.570 |

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

## 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 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, using the trade weight matrix (left three columns) and the distance weight matrix (right three columns).

Overall, three 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, especially markedly in the advanced-country subsample. Second, in most cases the model with both common factors and spatial effects exhibits the best performance. This accords with the finding in the preceding section that such model also offers the best in-sample fit. The main exception is the specification using the inverse distance weight matrix in the full-sample, under which the factor-only model does best at forecasting. Third, the factor-inclusive models with and without spatial effects exhibit very similar forecasting performance – in general, both outperform the spatial-only model (except for the 3-year forecast horizon in the full-sample, trade-matrix case), by a margin that is especially large in the advanced-country sample.

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

| | All countries | | | | | |
|---|---|---|---|---|---|---|
| | Trade weight matrix | | | Distance weight matrix | | |
| Forecast horizon | 1 year | 2 years | 3 years | 1 year | 2 years | 3 years |
| CSD specification | | | | | | |
| None | 2.870 | 4.605 | 3.733 | 2.870 | 4.605 | 3.733 |
| Factor only | 2.133 | 3.965 | 3.337 | 2.133 | 3.965 | 3.337 |
| Spatial only | 2.262 | 4.077 | 3.255 | 2.333 | 4.203 | 3.376 |
| Factor and spatial | 2.094 | 3.951 | 3.316 | 2.146 | 3.981 | 3.357 |
| | Advanced countries | | | | | |
| | Trade weight matrix | | | Distance weight matrix | | |
| None | 2.079 | 5.143 | 1.955 | 2.079 | 5.143 | 1.955 |
| Factor only | 1.541 | 4.562 | 1.016 | 1.541 | 4.562 | 1.016 |
| Spatial only | 1.930 | 5.045 | 1.671 | 1.926 | 5.050 | 1.690 |
| Factor and spatial | 1.521 | 4.498 | 0.957 | 1.491 | 4.475 | 0.999 |

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 and for the

two samples considered, growth 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, both contemporaneous and lagged – 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.

Our results also illustrate the consequences of improperly ignoring cross-sectional dependence when analyzing cross-country growth patterns. 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 the common factor, while still omitting spatial effects, helps correct these problems, but leaves evidence of residual dependence in the advanced-country sample. In turn, allowing for spatial effects, while omitting the common factor, also improves the fit and parameter estimates, but leads to overstated spatial effects, strong residual dependence, and – in virtually all scenarios considered – inferior forecasting performance.

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 forecasting. Overall, these results confirm the need to account for cross-sectional dependence, both strong and weak, in empirical modeling of growth across countries.

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# 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 | Australia | AUS |
| 2 | Algeria | DZA | 62 | Madagascar | MDG | Austria | AUT |
| 3 | Angola | AGO | 63 | Malawi | MWI | Belgium | BEL |
| 4 | Argentina | ARG | 64 | Malaysia | MYS | Canada | CAN |
| 5 | Australia | AUS | 65 | Mali | MLI | Denmark | DNK |
| 6 | Austria | AUT | 66 | Mauritania | MRT | Finland | FIN |
| 7 | Bahrain | BHR | 67 | Mauritius | MUS | France | FRA |
| 8 | Bangladesh | BGD | 68 | Mexico | MEX | Germany | DEU |
| 9 | Belgium | BEL | 69 | Mongolia | MNG | Greece | GRC |
| 10 | Benin | BEN | 70 | Morocco | MAR | Ireland | IRL |
| 11 | Bhutan | BTN | 71 | Mozambique | MOZ | Italy | ITA |
| 12 | Bolivia | BOL | 72 | Myanmar | MMR | Japan | JPN |
| 13 | Botswana | BWA | 73 | Namibia | NAM | Netherlands | NLD |
| 14 | Brazil | BRA | 74 | Nepal | NPL | New Zealand | NZL |
| 15 | Bulgaria | BGR | 75 | Netherlands | NLD | Norway | NOR |
| 16 | Burukina Faso | BFA | 76 | New Zealand | NZL | Portugal | PRT |
| 17 | Burundi | BDI | 77 | Nicaragua | NIC | Spain | ESP |
| 18 | Cambodia | KHM | 78 | Niger | NER | Sweden | SWE |
| 19 | Cameroon | CMR | 79 | Nigeria | NGA | Switzerland | CHE |
| 20 | Canada | CAN | 80 | Norway | NOR | United Kingdom | GBR |
| 21 | Chad | TCD | 81 | Oman | OMN | 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 | Korea, Dem. Peopl's R. | 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 | Sigapore | 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 | The first differnce of log real GDP | United Nations National Accounts |
| Bilateral Trade | Bilateral trade flow | IMF (DOTS) |
| Total factor productivity | Computed from Solow residual using labor and capital inputs | PWT |
| Trade openness | Sum of total exports and imports over GDP | WDI |
| Commodity intensity | Net Exports of Commodities over GDP | UN/COMTRADE |
| Exchange rate flexibility | De facto exchange rate regime | Gosh, Ostry and Qureshi (2015) |
| Financial depth | Domestic credit to private sector (% of GDP) | WB, WDI |
| Capital account openness | Chin-Ito Index of Capital account Liberalization | Chin-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) | WDI |
| Population | Average population in millions | United Nations National Accounts |

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

| Country | Trade | Distance | Country | Trade | Distance |
|---|---|---|---|---|---|
| Albania | 0.356 | 0.382 | Malawi | 0.001 | -0.023 |
| Algeria | 0.019 | 0.026 | Malaysia | 0.561 | 0.590 |
| Angola | 0.457 | 0.504 | Mali | 0.046 | -0.027 |
| Argentina | 0.344 | 0.383 | Mauritania | 0.162 | 0.177 |
| Australia | 0.206 | 0.183 | Mauritius | 0.275 | 0.337 |
| Austria | 0.632 | 0.523 | Mexico | 0.665 | 0.544 |
| Bahrain | 0.392 | 0.334 | Mongolia | 0.645 | 0.659 |
| Bangladesh | 0.234 | 0.326 | Morocco | -0.149 | -0.201 |
| Belgium | 0.660 | 0.613 | Mozambique | 0.525 | 0.457 |
| Benin | -0.088 | -0.077 | Myanmar | 0.566 | 0.554 |
| Bhutan | 0.270 | 0.312 | Namibia | 0.444 | 0.344 |
| Bolivia | 0.645 | 0.693 | Nepal | -0.137 | -0.141 |
| Botswana | 0.505 | 0.596 | Netherlands | 0.733 | 0.598 |
| Brazil | 0.617 | 0.630 | New Zealand | 0.345 | 0.345 |
| Bulgaria | 0.634 | 0.645 | Nicaragua | 0.268 | 0.290 |
| Burkina Faso | -0.029 | -0.086 | Niger | 0.053 | 0.051 |
| Burundi | 0.117 | 0.102 | Nigeria | 0.478 | 0.465 |
| Cambodia | 0.565 | 0.571 | Norway | 0.639 | 0.601 |
| Cameroon | 0.501 | 0.516 | Oman | 0.180 | 0.150 |
| Canada | 0.742 | 0.683 | Pakistan | 0.133 | 0.176 |
| Chad | 0.265 | 0.278 | Panama | 0.360 | 0.372 |
| Chile | 0.495 | 0.528 | Paraguay | 0.473 | 0.477 |
| China | 0.029 | 0.053 | Peru | 0.495 | 0.500 |
| Colombia | 0.671 | 0.690 | Philippines | 0.642 | 0.620 |
| Comoros | 0.044 | 0.147 | Poland | 0.623 | 0.630 |
| Costa Rica | 0.612 | 0.588 | Portugal | 0.688 | 0.597 |
| Cyprus | 0.446 | 0.482 | Qatar | 0.543 | 0.532 |
| Cote d'Ivoire | 0.355 | 0.348 | Korea, Dem. Peopl's R. | 0.417 | 0.404 |
| Congo, Dem. Rep | 0.746 | 0.774 | Romania | 0.778 | 0.794 |
| Denmark | 0.548 | 0.472 | Saudi Arabia | 0.443 | 0.510 |
| Djibouti | 0.165 | 0.210 | Senegal | -0.127 | -0.170 |
| Dominican Republic | 0.448 | 0.474 | Sierra Leone | 0.399 | 0.397 |
| Ecuador | 0.483 | 0.501 | Sigapore | 0.602 | 0.627 |
| Egypt | 0.269 | 0.301 | South Africa | 0.644 | 0.641 |
| El Salvador | 0.748 | 0.715 | Spain | 0.811 | 0.760 |
| Ethiopia | 0.383 | 0.373 | Sri Lanka | 0.259 | 0.223 |
| Fiji | 0.000 | 0.017 | Sudan | 0.218 | 0.213 |
| Finland | 0.688 | 0.674 | Swaziland | 0.445 | 0.418 |
| France | 0.764 | 0.714 | Sweden | 0.547 | 0.470 |
| Germany | 0.645 | 0.598 | Switzerland | 0.605 | 0.565 |
| Ghana | 0.469 | 0.479 | Syria | 0.318 | 0.322 |
| Greece | 0.568 | 0.557 | Thailand | 0.557 | 0.534 |
| Guatemala | 0.855 | 0.880 | Togo | 0.203 | 0.198 |
| Guinea | 0.104 | 0.086 | TrinidadTobago | 0.703 | 0.692 |
| Guinea-Bissau | -0.211 | -0.184 | Tunisia | 0.298 | 0.284 |
| Haiti | 0.191 | 0.221 | Turkey | 0.309 | 0.296 |
| Honduras | 0.579 | 0.548 | Uganda | 0.517 | 0.525 |
| Hong Kong | 0.572 | 0.681 | United Arab Emirates | 0.417 | 0.468 |
| Hungary | 0.658 | 0.668 | United Kingdom | 0.516 | 0.374 |
| India | 0.015 | 0.035 | United Republic,Tanzania | 0.515 | 0.472 |
| Indonesia | 0.495 | 0.465 | United States | 0.601 | 0.605 |
| Iran | 0.383 | 0.375 | Uruguay | 0.626 | 0.687 |
| Ireland | 0.419 | 0.408 | Venezuela | 0.427 | 0.441 |
| Isreal | 0.409 | 0.402 | Viet Nam | 0.252 | 0.283 |
| Italy | 0.720 | 0.645 | Zambia | 0.336 | 0.329 |
| Jamaica | 0.416 | 0.322 | **Median** | **0.448** | **0.465** |
| Japan | 0.624 | 0.580 | | | |
| Jordan | 0.508 | 0.511 | | | |
| Kenya | 0.495 | 0.479 | | | |
| Lao PDR | 0.041 | 0.019 | | | |
| Lesotho | 0.271 | 0.252 | | | |
| Madagascar | -0.042 | -0.143 | | | |

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

| **Country** | **Trade** | **Distance** |
|---|---|---|
| Australia | 0.338 | 0.331 |
| Austria | 0.705 | 0.677 |
| Belgium | 0.755 | 0.745 |
| Canada | 0.793 | 0.780 |
| Denmark | 0.709 | 0.712 |
| Finland | 0.829 | 0.841 |
| France | 0.850 | 0.859 |
| Germany | 0.767 | 0.808 |
| Greece | 0.644 | 0.646 |
| Ireland | 0.682 | 0.598 |
| Italy | 0.822 | 0.828 |
| Japan | 0.701 | 0.721 |
| Netherlands | 0.823 | 0.814 |
| NewZealand | 0.320 | 0.327 |
| Norway | 0.638 | 0.663 |
| Portugal | 0.805 | 0.806 |
| Spain | 0.880 | 0.874 |
| Sweden | 0.729 | 0.751 |
| Switzerland | 0.641 | 0.655 |
| UnitedKingdom | 0.711 | 0.728 |
| UnitedStates | 0.779 | 0.816 |
| **Median** | **0.729** | **0.745** |

## Appendix B: Bias correction procedure

Here we briefly summarize the bias correction proposed by Shi and Lee (2017). In order to derive the limiting distribution of the estimators $\hat{\eta}_T$ and the associated asymptotic bias, consider $G(\eta) = \frac{1}{nT}\sum_{i=r+1}^{n}\mu_i(S - \sum_{k=1}^{K} Z_k\delta_k)(S - \sum_{k=1}^{K} Z_k\delta_k)'$ from equation (5) is expressed around the initial value $\eta_0$. Under appropriate assumptions, using the perturbation theory of linear operators the limiting distribution of $\hat{\eta}$ around $\eta_0$ can be derived as

$$\sqrt{nT}(\hat{\eta} - \eta_0) - (\sigma_0^2 Q)^{-1}\varphi \xrightarrow{d} N(0, Q^{-1}(Q+\Sigma)Q^{-1}), \qquad (A1)$$

where $\varphi = (\varphi_\beta, \varphi_\lambda, 0_1 \times (K-2), \varphi_\rho)'$, with $\varphi_\beta = -\frac{\sigma_0^2}{\sqrt{nT}}\sum_{h=1}^{T-1} tr(J_0 P_{F_T} J_h')tr(A^{h-1}S^{-1})$
$\varphi\lambda = -\frac{\sigma^2\_0}{\sqrt{nT}}\sum_{h=1}^{T-1} tr(J_0 P_{F_T} J_h')tr(WA^{h-1}S^{-1})$,
$\varphi\rho = -\frac{\sigma_0^2}{\sqrt{nT}}\sum_{h=1}^{T-1} tr(J_0 P_{F_T} J_h')tr(\beta G + \lambda GW)A^{h-1}S^{-1} + \sqrt{\frac{T}{n}}\sigma_0^2(\frac{r_0}{n}tr(G - tr(P_\psi G))$,
$A = S^{-1}(\beta I + \lambda W),\ S = I - \rho W,\ G = WS^{-1},\ J_h = (0_{T\times(T-h)}, I_T, 0_{T\times h})'$,

$$Q_T = \frac{1}{nT\sigma_0^2}\pi_T'\pi_T + \begin{pmatrix} 0 & \dots & & 0 & 0 \\ \vdots & & & \vdots & \vdots \\ 0 & \dots & 0 & 0 & 0 \\ 0 & \dots & 0 & \Upsilon_{K+1,K+1} & \Upsilon_{K+1,K+2} \\ 0 & \dots & 0 & \Upsilon_{K+1,K+2} & \Upsilon_{K+2,K+2} \end{pmatrix}$$

where $\pi_T = (\pi_1 \dots \pi_{K+1}\, 0)$, with $\pi_k = vec(M_T Z_k M_F), k = 1, \dots, K+1$;
$\Upsilon_{K+1,K+1} = \frac{1}{n}tr(GG') + \frac{1}{n}tr(G^2) - 2(\frac{1}{n}tr(G))^2$,
$\Upsilon_{K+1,K+2} = \frac{1}{n}tr(G\tilde{G}) + \frac{1}{n}tr(\tilde{G}^2) - 2(\frac{1}{n}tr(\tilde{G}))^2$
$\Upsilon_{K+2,K+2} = \frac{1}{n}tr(\tilde{G}'\tilde{G}) + \frac{1}{n}tr(\tilde{\tilde{G}}^2) - 2(\frac{1}{n}tr(\tilde{G}))^2$, and the expression for $\Sigma$ is given in Shi and Lee (2017).

Equation (A1) indicates that the limiting distribution of $\hat{\eta}$ may deviate from $\eta_0$ with an asymptotic bias term $(\sigma_0^2 Q)^{-1}\varphi$. In our SDPD the bias comes from the predetermined control variables and the interactions of the spatial effects and factor loadings.

Under some additional assumptions, the bias corrected estimator is given by

$$\hat{\eta}^{bc} = \hat{\eta} - (\hat{\sigma}^2\hat{Q})^{-1}\frac{1}{\sqrt{nT}}\hat{\varphi}.$$