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Assessing the International Comovement of Equity Returns

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Abstract

The international comovement of equity returns has been viewed as reflecting either pervasive common shocks or local linkages between countries. This paper brings these perspectives together by assessing the comovement of equity returns in a dynamic model that allows for both common factors and spatial dependence, using quarterly data for 40 advanced and emerging countries over the past two decades, and including GDP growth, the real interest rate, and credit as fundamental variables. Estimation results employing a bias-corrected quasi-maximum likelihood approach provide strong indication that the cross-country dependence of equity returns results from both spatial effects and common shocks captured by a latent common factor—weak and strong dependence, respectively. The factor exhibits a robust negative correlation with market measures of aggregate risk. Countries' exposure to the common factor rises with their extent of trade openness and the degree of rigidity of their exchange rate regime. Despite its simplicity, the empirical model fits the data well. All these results are robust to the use of alternative spatial weight matrices. The paper also shows that ignoring cross-country dependence leads to distorted parameter estimates and a marked deterioration of the explanatory power of the empirical model.

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1 Introduction

The international synchronization of asset prices has attracted increasing attention in recent years. From the macroeconomic perspective, it represents a mechanism for the cross-country propagation of shocks, a matter of concern especially after the global financial crisis. From the finance perspective, it detracts from the presumed benefits of international portfolio diversification. Asset price synchronization has been on a rising trend, especially in the case of equity markets. Christoffersen, Errunza, Jacobs, and Langlois (2012) find that international dependence between stock markets has trended significantly upward since the 1970s, for both advanced and emerging countries. Jorda, Schularick, Taylor and Ward (2017), using data for 17 advanced countries spanning 150 years, find a marked long-run rise in the degree of international comovement of equity prices, above and beyond the comovement of the prices of other assets such as housing and debt. Using the same data, Bekaert and Mehl (2017) similarly find an increase in the conditional betas averaged across countries, in both value-weighted and unweighted terms. In turn, Cotter, Gabriel and Roll (2018) conclude that common global factors account for an increasing share of the variance of equity, bond and real estate returns across developed and emerging markets.

Much of the empirical literature attributes the international dependence of asset prices to pervasive shocks affecting a multitude of countries. A number of recent contributions view the shocks as reflecting a global financial cycle driven primarily by shifts in international investors' risk aversion – as well as monetary policy in center countries, notably the U.S. (see e.g., Rey (2013), Miranda-Agrippino and Rey (2018), Bruno and Shin (2015), Xu (2017)).[1] Empirically, the shocks driving asset prices across the world are typically modeled as latent common factors or, alternatively, summarized by a handful of variables capturing global financial conditions. This literature goes on to assess the determinants of countries' exposure to the global financial cycle, with particular attention to the insulating role of flexible exchange rates; see for example Rey (2013) and Bekaert and Mehl (2017).

Another strand of empirical literature has attributed the international comovement of asset prices to real and financial linkages between countries.[2] Bayoumi, Fazio and MacDonald (2007) show that bilateral geographic distance can account for much of the observed variation in the pairwise correlation of equity price indices across a sample of emerging markets.[3] Forbes and Chinn (2004) assess how trade and financial linkages between five center countries and 40 other countries shape the response of the latter countries' equity market returns to those of the former, concluding that bilateral trade plays the biggest role. Didier, Love and Martinez-Peria (2012) examine the

[1] Similarly, Forbes and Warnock (2012) stress the role of global investors' risk aversion for the international comovement of capital flows, while Barrot and Servén (2018) and Cerutti, Claessens and Rose (2017) evaluate the quantitative relevance of the global financial cycle for the observed patterns of flows.

[2] In a similar vein, several papers have highlighted the role of bilateral linkages in the international propagation of sovereign and banking crises. Bolton and Jeanne (2011) stress banks' holdings of foreign sovereign debt as a key mechanism in the propagation of the Eurozone crisis. Hale, Kapan and Minoiu (2016) likewise document how interbank loans help transmit distress across national banking systems.

[3] Chong, Wong, and Zhang (2011) likewise relate the pairwise correlations across a sample of advanced and emerging countries to bilateral distance plus other gravity variables, and find that distance has a robust negative effect.

comovement of market returns of a large number of countries with U.S. returns during the global financial crisis, and find that bilateral financial linkages were the primary drivers. Asgharian, Hess and Liu (2013) use spatial econometrics techniques to explore the role of a variety of bilateral linkages (geographic, macroeconomic and financial) for the commonality of the returns of 41 stock markets. Bilateral trade emerges as the most important link.[4]

While both of these literatures are concerned with the cross-country dependence of equity (and other asset) prices, methodologically they take very different views. The first literature stresses shocks with worldwide reach. In contrast, the second literature emphasizes interdependence between particular countries. These two views roughly correspond to the distinction between strong and weak cross-sectional dependence, respectively. Strong dependence arises from common shocks. Weak dependence reflects local interactions.[5] Strong dependence is typically analyzed with factor models (as done, for example, by Miranda-Agrippino and Rey (2018), Xu (2017) or Cotter, Gabriel and Roll (2018) for asset prices), while weak dependence is typically analyzed with spatial models highlighting geographic or economic distance (as in, e.g., Asgharian, Hess and Liu (2013)).

So far, the empirical literature 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 example, ignoring strong dependence when it is present may lead to inconsistent estimates if the omitted common factors are correlated with the 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. Ignoring spatial dependence in the error term 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. Thus, from the viewpoint of empirical modeling, the two perspectives should be viewed as complementary, rather than mutually exclusive.

In this paper we bring both approaches together. We analyze the international comovement of aggregate equity returns in a sample of 40 advanced and emerging countries, using an encompassing empirical framework including both spatial effects and common factors. This allows us to assess the respective roles of strong and weak cross-sectional dependence, and to illustrate the consequences of unduly omitting either (or both) of them. To date, very few papers have employed a similarly flexible

[4] Aside from these direct links, indirect linkages across asset markets in different countries may also arise from the presence of common investors. As they adjust their international portfolio holdings in response to shocks, common investors become a source of asset price comovement (see, e.g., Broner, Gelos and Reinhart (2006)). The empirical relevance of this propagation mechanism has received special attention in the case of international mutual funds (e.g., Raddatz and Schmukler (2012)).

[5] 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).

methodological framework; the notable exception is Bailey, Holly and Pesaran (2016), who examine the patterns of house prices across U.S. metropolitan areas.

We assume that spatial interactions occur through equity returns, which seems a natural way to model the interconnectedness of investors' portfolios. However, this implies that the two-step estimation methods employed by Bailey, Holly and Pesaran (2016), which assume that the interaction occurs through the spatial error, are not applicable to our setting. Instead, we use a quasi-maximum likelihood estimation approach recently developed by Shi and Lee (2017) that permits joint consideration of common factors and spatial dependence in a dynamic framework. Because the factors and their loadings are treated as parameters, whose number grows with sample size, they create a nuisance parameter problem. To address it, we use the bias correction procedure proposed by Shi and Lee (2017).

In light of the earlier literature, we experiment with alternative specifications of the spatial weight matrix summarizing interactions between countries. We use a bilateral trade weight matrix to capture real linkages across countries, and a bilateral foreign investment weight matrix to assess their financial linkages. In addition, we also present results using a bilateral geographical distance weight matrix.

Because our sample contains both advanced and emerging countries, and the degree of development of financial markets – as well as the extent of financial and real integration in the global economy – differs between both groups, we also estimate the empirical model of equity returns on a sub-sample of 25 advanced countries. This allows us to assess differences across both groups in the role of the various drivers of equity prices, as well as the extent of cross-sectional dependence.

Consistent with theoretical expectations, we find that real equity returns are positively related to real GDP growth, and negatively related to changes in the real interest rate and – in the extended country sample only – real credit growth, which suggests that in emerging countries with less-developed financial markets interest rates do not suffice to capture the financial environment faced by investors. These results show little variation across the three alternative specifications of the spatial weight matrix.

We also find strong evidence of spatial effects, summarized by a positive contemporaneous spatial lag and a negative spatial-time lag. Both are statistically significant in virtually all specifications, implying that local interactions are important to understand the international comovement of equity returns. In addition, equity returns reflect a common factor that is strongly positively correlated with average returns, and strongly negatively correlated with measures of aggregate risk, in line with the results of, e.g., Rey (2013), Miranda-Agrippino and Rey (2018), and Xu (2017).

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 equity returns is bigger in countries with more open trade accounts and more rigid exchange rate regimes. The latter result implies that, notwithstanding their worldwide reach, the choice of exchange rate regime still matters for countries' exposure to global financial shocks – which echoes the recent findings of Bekaert and Mehl (2017) and Barrot and Servén (2018).

Finally, we shed light on the importance of properly taking into account cross-sectional dependence. Ignoring it, by omitting both common factors and spatial

effects, leads to a gross overstatement of the procyclical behavior of equity returns. It also weakens dramatically the estimated model's empirical performance. Including the common factor, while still omitting spatial effects, greatly helps correct these problems, at the cost of remaining residual (weak) dependence. In turn, allowing for spatial effects, while omitting the common factor, also improves the model fit, but leads to overstated spatial effects – exaggerating the propagation of shocks through local linkages – and strong residual dependence. Overall, these results confirm the need to account for cross-sectional dependence, both strong and weak, in empirical modeling of equity returns across countries.

The rest of the paper is organized as follows. Section 2 lays out the factor-augmented dynamic spatial model of equity returns employed in the paper. Section 3 presents the data. Section 4 reports the results, and the final section provides conclusions.

2 Analytical framework

To study the comovement of equity returns, we use a dynamic model that allows for both common factors and spatial dependence. This section describes the model and summarizes our estimation approach.

2.1 A factor-augmented dynamic spatial model of equity returns

Let g_{it} denote the real equity returns in country $i = 1, \ldots, n$ at time $t = 1, \ldots, T$, and let $g_t = (g_{1t}, ..., g_{nt})'$. Following Shi and Lee (2017), we assume that g_t follows a spatial dynamic panel data (SDPD) model of the form:

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

Thus, each country's real equity return is related to current real equity returns in (economically) neighboring countries, Wg_t, where W is an $n \times n$ spatial weight matrix; lagged equity returns in the own country, g_{t-1}, as well as in neighboring countries Wg_{t-1}; a set of observable explanatory variables X_t; 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 and unobserved common factors. 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 equity returns of nearby countries on the equity returns of a particular country. The extent of spatial dependence is measured by the contemporaneous spatial autoregressive parameter ρ and the space-time lag coefficient λ.[6] 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 stock returns across all countries. The $n \times r$ matrix of factor loadings Ψ measures the (possibly

[6]The parameter λ, termed 'diffusion parameter' by Shi and Lee (2017), captures spatio-temporal correlations in equity returns that may result from partial adjustment or inter-temporal decision making by investors, see e.g., Tao and Yu (2012).

heterogeneous) effect of the factors on each country's equity returns.

The X variables comprise a set of macroeconomic fundamentals of equity returns. Following the standard valuation model, which states that equity returns are given by the present discounted value of expected future cash flows, we include in X the rate of growth of real GDP, which has been found to account for much of the variation in expected cash flows (e.g., Fama (1990)), and (the first difference of) the real interest rate, which affects the risk premium and the discount rate employed to bring future cash flows to present value terms, and therefore has a negative effect on equity returns (Chen, Roll and Ross (1986), Jensen and Johnson (1995)). Moreover, because the empirical sample employed in the paper includes countries with relatively undeveloped financial markets, in which observed interest rates may not reflect accurately the cost of financing, we add among the X variables the rate of growth of the real stock of credit to the private sector, to better capture financial conditions.

The SDPD in 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 equity returns to observable fundamentals plus latent common factors.[7]

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 $g_t = Ag_{t-1} + S^{-1}(X_t\theta + \Psi f_t + V_t)$. Recurrent substitution yields

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

With a row-normalized spatial weight matrix W, the sequence $\{A^h\}_{h=0}^{\infty}$ is summable in absolute values, 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).[8]

Equation (2) shows that shocks to the error term and the explanatory variables in a particular location are propagated to all other units within the spatial system in

[7] 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

$$g_t = \rho\, Wg_t + \beta g_{t-1} + \lambda\, Wg_{t-1} + X_t\theta + \zeta + \iota\xi_t + \varepsilon_t,$$

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

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

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

accordance with the structure of the weight matrix, so that their impact diminishes with (economic) distance.

2.2 Estimation approach

Estimation of the model (1) poses some special issues due to its simultaneous consideration 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. Below 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 and Appendix B for a brief summary.

In equation (1), let $Z_t = (g_{t-1}, Wg_{t-1}, X_t)$. Define the parameters of the model as $\eta = (\delta', \rho)'$ with $\delta = (\beta, \lambda, \theta')'$, σ^2, Ψ and F_T. 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

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

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 Ψ 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, specifically due both to the presence of predetermined regressors (the lagged dependent variable) and to the interaction between the spatial effects and the factor loadings. To tackle this problem, Shi and Lee (2017) develop a bias correction that yields an asymptotically normal, properly-centered estimator. The estimations reported below using common factors employ the bias-corrected estimator.

3 Data

We assess the international comovement of equity returns using a balanced panel data set comprising 40 advanced and emerging countries over 1995:1 to 2016:3 – a total of 3,480 quarterly observations. Because advanced countries tend to exhibit higher real and financial openness, as well as larger and more liquid financial markets, than other countries, we consider separately a subsample of 25 advanced economies, comprising 2,175 observations. Table A1 in the appendix provides the complete list of countries.

Following Hirata, Kose, Otrok and Terrones (2013), we measure equity prices by the stock market price index for each country. Real equity returns are then given by the first difference of the log of equity prices deflated by the consumer price index.[9]We collect the equity price index data from the OECD Statistics Database, except in the cases of Argentina, Hong Kong and Peru, for which we draw the data from Investing.com.[10]

Figure 1 depicts the cross-country average of the real equity returns. It displays very similar fluctuations over the two country samples, including a sharp decline around the fourth quarter of 2008, at the onset of the global crisis.

As already mentioned, we consider three covariates of equity returns: real GDP, short term interest rates and private credit. The GDP data comes from the OECD Statistics Database and the International Financial Statistics (IFS) of IMF and complemented with national statistics sources as well as the Federal Reserve Bank of St. Louis Economic Data (FRED). Credit is measured by domestic credit to the private sector, drawn from DataStream, complemented with FRED and the Bank for International Settlements (BIS). All the variables are measured in real terms, using the consumer price index as deflator.

[9]An alternative would be to express equity returns in nominal terms in a common currency – e.g., U.S. dollars. However, this would automatically introduce additional commonality in the returns across countries, reflecting the movements in the exchange rate of the currency in question. To avoid it, we opt for working with real returns instead.

[10]For Argentina we use the Merval stock price index, for Hong Kong we use the Hang Seng stock market index, and for Peru we use the S&P/BVL Peru General Index.

Figure 1: Mean equity returns

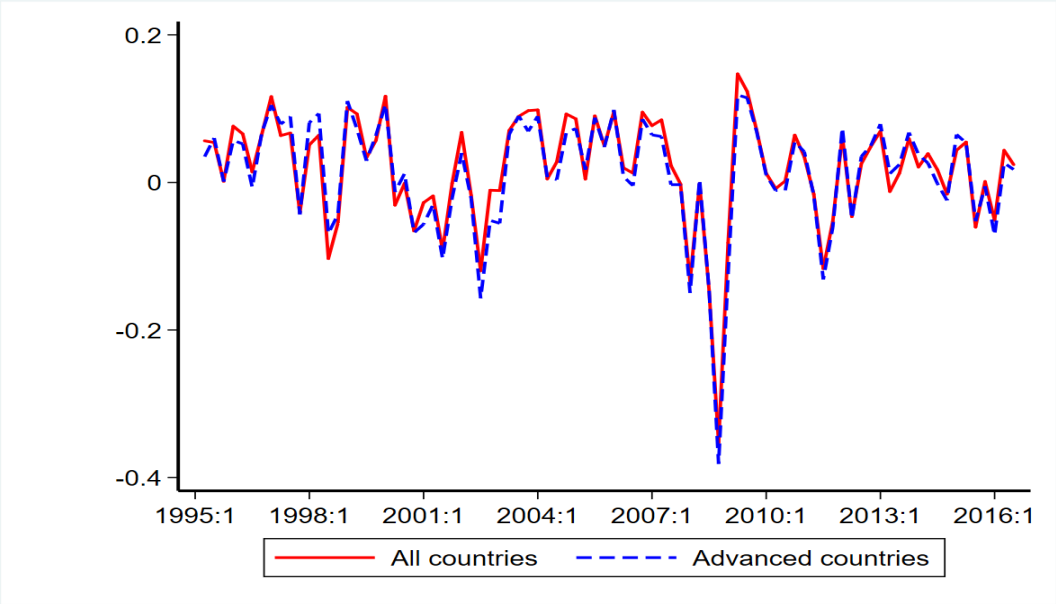


Table 1: Descriptive statistics

	Advanced countries				All countries			
	Mean	Std.dev	Min.	Max.	Mean	Std.dev	Min.	Max.
Equity returns	0.013	0.100	-1.246	0.463	0.018	0.109	-1.246	0.643
GDP growth	0.003	0.018	-0.057	0.764	0.004	0.017	-0.123	0.764
Δ Real interest rate	-0.001	0.008	-0.095	0.100	-0.025	0.406	-0.152	0.013
Real credit growth	0.015	0.023	-0.120	0.369	0.022	0.035	-0.387	0.572
N		2175				3480		

Notes: Equity returns are measured by the first difference of the log of real equity price indices, GDP growth is the first difference of the log of real GDP, Δ Real interest rate is the first difference of the real interest rate, and Real credit growth is the first difference of the log of the real credit stock. The sample period covers 1995:1-2016:3.

Table 1 reports summary statistics of real equity returns, real GDP growth, the growth rate of the real credit stock, and the first difference of the real interest rate. Except for the latter variable, all exhibit higher means in the full sample than in the advanced-country sample. Likewise, all the variables show higher volatility in the former than in the latter sample, with the exception of the GDP growth rate. The large equity return growth outlier shown in the table corresponds to the collapse of Iceland's stock market at the time of the global financial crisis.

Descriptive statistics of real equity returns for the individual countries are reported in Table A3 in the appendix. The mean and standard deviation exhibit considerable variation across countries. The mean ranges from 6.5% in Turkey to -0.5% in Greece, while the standard deviation ranges from a low value of 5.1% in New Zealand to a high value of 18.9% in Iceland.

The spatial weight matrix that connects cross-sectional units is a key element in the empirical implementation of the model. We experiment with three alternative specifications. First, 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). For the Czech Republic, Hungary, Poland, Slovakia and Slovenia, the trade data is collected from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) online database. 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 re-scaled dividing each of its elements by the sum of its corresponding row, so that the rows of the rescaled matrix sum to unity.[11]

The second specification of the spatial weight matrix is based on bilateral foreign direct investment (FDI) positions.[12] The underlying logic is that the higher is the share of outward and/or inward investments of country i from country j, the more economically interdependent countries i and j are, resulting in larger spillovers from one country to the other; see, for instance, Asgharian, Hess and Liu (2013) and Chinn and Forbes (2004).

We construct the bilateral FDI weight matrix in a similar fashion to the bilateral trade weight matrix, using data on bilateral FDI positions taken from the OECD International Direct Investment Statistics, and replacing imports and exports in the above definition of W_{ij} with the stock of outward foreign direct investment from country i to country j and the stock of inward foreign direct investment from country j to country i, respectively.

Finally, the third specification of the weight matrix is based on pure geographical distance. In particular, following Ertur and Koch (2007), we use a weight matrix WD based on inverse squared distance.[13] 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.[14]

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

[12] Ideally, we would want to use the bilateral positions of countries' international portfolios, rather than just their FDI positions. However, such information is not available for our sample coverage.

[13] We also experimented with a matrix based on the negative exponential of squared distance. The results were very similar to those obtained with inverse squared distance, and to save space they are not reported.

[14] The great-circle distance, the shortest distance between any two country capitals, is computed as: $d_{ij} = radius \times$

To explore the relation between the common factor(s) and the 'push' variables taken in the literature as indicators of global financial conditions (as in, e.g., Miranda-Agrippino and Rey (2018)), we collect data on several measures of investors' risk perceptions – the Chicago Board Options Exchange Market Volatility Index (VIX), the Bank of America Merrill Lynch high-yield spread, the Bank of America Below Options-Adjusted Spread, and Moody's corporate bond yield spread. In addition, we also use the U.S. Federal Funds real interest rate, as well as the real effective exchange rate of the U.S., taken from FRED, and the risk appetite index of Bekaert, Engstrom, and Xu (2017).

To assess the covariates of countries' factor loadings, we collect information on selected policy and structural indicators of capital account openness, financial depth, stock market capitalization and the exchange rate regime. Following Barrot and Servén (2018), capital account openness is measured by the Chinn-Ito index, and financial depth is measured by domestic credit to the private sector as a percentage of GDP. Stock market capitalization is measured as the total value of all listed shares in a stock market as a percentage of GDP. Following Ghosh, Ostry, Kapan and Qureshi (2015), the exchange rate regime is categorized into three groups, and each is assigned a numeric value so that higher values denote more flexible regimes – i.e., Peg = 1, Intermediate = 2, and Float = 3. Table A2 in the appendix presents the data description, sources and other details.

4 Empirical results

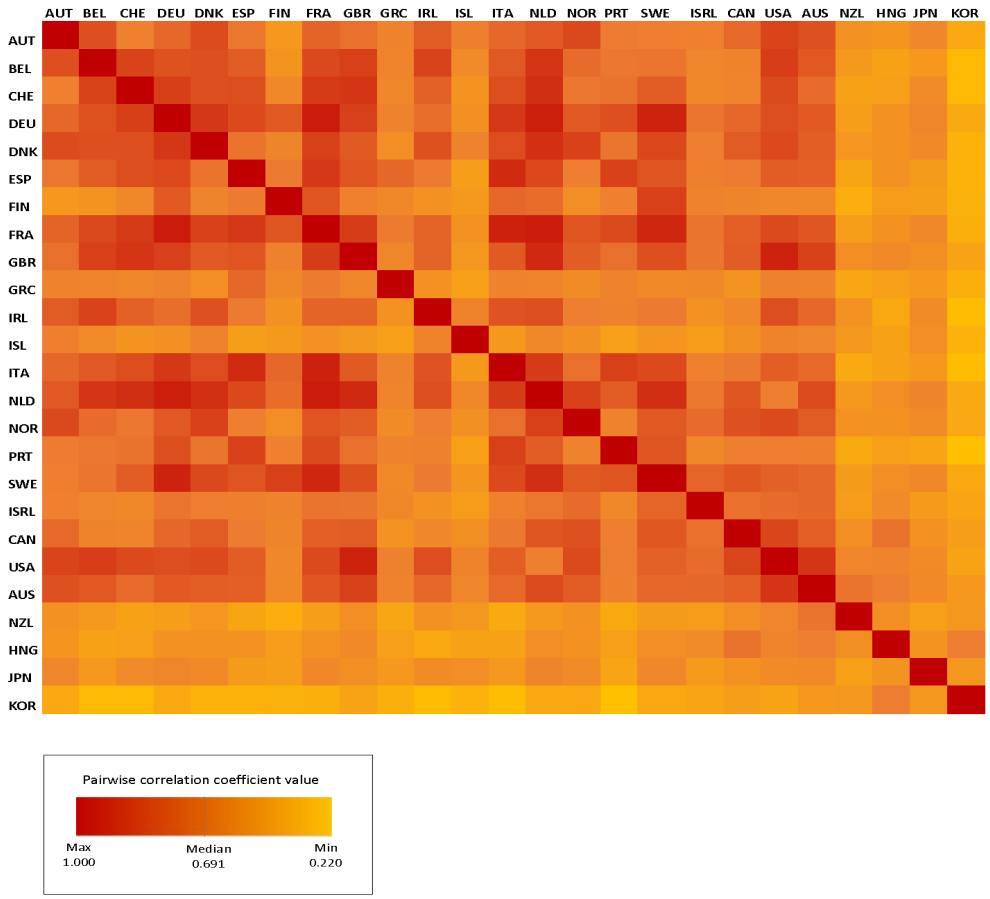
Before proceeding with the estimation of the model, we examine the cross-country comovement of equity returns in the data. The average pairwise correlation of real equity returns equals .51 for the full sample and .67 for the advanced-country sample. A total of 754 of the 780 distinct pairwise correlations in the full country sample are positive, and 652 of them are statistically significant at the 5 percent significance level.[15] In turn, all of the 300 distinct pairwise correlations in the advanced-country sample are positive, and all are significantly different from zero at the 5 percent significance level. Overall, these figures reveal strong international comovement of equity returns, particularly among advanced countries.[16]

$cos^{-1}[cos\,|long_i - long_j|\,coslat_i costlat_j + sinlat_i sinlat_j]$ 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.

[15] We approximate the standard error of a correlation coefficient r by $\sqrt{\frac{1-r^2}{T-1}}$.

[16] This result is in line with a large number of studies (e.g., Bekaert and Mehl (2017), Jorda, Schularick, Taylor and Ward (2017), Bekaert, Harvey, Kiguel and Wang (2016), Rey (2013), and Bekaert, Hodrick, and Zhang (2009)) that find significant comovement of asset returns across countries.

Figure 2: Heat map: Cross-country correlation of equity returns



The heat map in Figure 2 illustrates the patterns of the pairwise correlation of equity returns for the advanced-country sample.[17] Darker colors indicate higher correlations. The correlations in the figure range from .22 (corresponding to the Korea-Portugal pair) to .94 (the France-Germany correlation), with a median of .69. Visual inspection reveals that the correlations are consistently very high among European countries, whose equity returns appear to be tightly linked, except for Iceland, Finland and Greece. In contrast, with the exception of Australia, in the Asia-Pacific countries shown at the bottom of the graph equity returns bear a much weaker relation with those of other countries.

While the pairwise correlations provide a strong hint of cross-sectional dependence in the data, 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 simple averages of pairwise correlation coefficients. Specifically, 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

[17] To save space, we do not report the heat map of the full sample.

cross-sectional average of the observations. Specifically, the exponent α is given by $Std.(\tilde{x}_t) = O(N^{\alpha-1})$, where $\tilde{x}_t$ is a simple cross-sectional average of observations $x_{it}, i = 1, 2, ...n; t = 1, 2, ..., T$. The exponent 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.[18]

Table 2 reports the Pesaran CD test statistic and the exponent of cross-sectional dependence of the dependent and independent variables of the model, for both the advanced-country and the full sample. The CD test statistic for equity returns is above 100 for both samples, overwhelmingly rejecting the null. For the other variables, the statistic also provides evidence against weak dependence, although to a more limited extent. In both country samples, the highest CD statistic, aside from that of equity prices, corresponds to GDP growth.

Table 2: Cross-sectional dependence

	Advanced countries			
	Equity returns	GDP growth	Δ Real interest rate	Real credit growth
Pesaran CD statistic	104.788	13.091	11.340	7.905
Exponent of CSD	1.002	0.961	0.892	0.861
	(0.905, 1.099)	(0.907, 1.015)	(0.823, 0.960)	(0.822, 0.899)
	All countries			
Pesaran CD statistic	131.365	63.542	10.529	39.201
Exponent of CSD	0.983	0.973	0.829	0.941
	(0.879, 1.085)	(0.839, 1.106)	(0.796, 0.862)	(0.892, 0.991)

Notes: Equity returns are measured by the first difference of the log of real equity price indices, GDP growth is the first difference of the log of real GDP, Δ Real interest rate is the first difference of the real interest rate, and Real credit growth is the first difference of the log of the real credit stock. 'Exponent of CSD' is the exponent of cross-sectional dependence, and values in parenthesis are its 95% confidence bands. The sample period covers 1995:1-2016:3.

Table 2 also reports the exponent of cross-sectional dependence along with 95% confidence bands, for both the advanced and full country samples. For equity prices, the estimated value of α is 1 in the advanced-country sample and .98 in the full sample. In both cases, the 95% confidence region reaches well above 1, providing clear indication of the presence of strong common factors in the equity returns data.

The table also shows that the exponent of cross-sectional dependence of GDP growth is very close to 1 in both country samples, with the confidence region including unity in both cases. This agrees with the evidence that GDP growth around the world reflects a common factor (Kose, Otrok and Whiteman (2003)). Finally, for the interest rate and credit variables the estimated exponents of cross-sectional dependence are below .9,

[18] In a portfolio setting, the degree of cross-sectional dependence of asset returns can be viewed as a measure of the extent of risk (non-)diversification associated with an equally-weighted portfolio. More broadly, 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).

except in the case of credit in the full country sample. However, for neither of them does the 95% confidence region include 1.

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 use information criteria. Following Choi and Jeong (2018), we compute the IC_{p2}, BIC and HQ criteria, setting the maximum number of factors to 3.[19]

For both the full and the advanced-country samples, we perform this calculation using in turn each of the three spatial weight matrices considered. However, the results are invariant to the choice of weight matrix. For both country samples, the BIC and HQ criteria select one factor. In turn, the IC_{p2} criterion selects two factors in the full sample, and three in the advanced-country sample. We opt for employing one factor in all the estimations below.[20]

We next turn to the main estimation results. Table 3 reports model estimates for both the full sample (top panel) and the advanced-country sample (bottom panel). The three columns of the table correspond to the three alternative specifications of the spatial weight matrix – bilateral trade, bilateral foreign direct investment, and bilateral inverse distance.

Consider first the full-sample results in the top panel of the table. Across all specifications, the coefficient of the lagged dependent variable is positive and statistically significant, indicating a significant degree of inertia in equity returns. In turn, both real GDP growth and the change in the real interest rate carry significant coefficients, positive and negative, respectively, in accordance with theoretical expectations. In addition, the coefficient on credit growth is also positive and significant, consistent with the view that the interest rate does not suffice to capture financial conditions in the sample countries, likely due to financial market frictions; hence credit growth provides independent information on the financial environment faced by equity investors. Moreover, the estimated coefficients of these variables are very similar across the three specifications of the spatial weight matrices.

As for the spatial effects, the parameter estimate of the contemporaneous spatial lag is consistently positive, while that of the space-time lag is negative; their magnitude is largest under the bilateral trade weight matrix. The positive contemporaneous spatial lag implies that higher equity returns in a given country tend to raise those of neighboring countries through bilateral financial linkages. In turn, the negative sign of the space-time lag accords with the pattern commonly found in dynamic models with spatial effects.[21] The estimated spatial effects are significant in all cases except for the space-time lag under the bilateral FDI weight matrix. The implication is that information

[19] Setting the maximum number of factors to 5 instead yields very similar results.

[20] Because the factors and loadings are identified only up to a sign change, in the estimation we set their respective signs so that the sample country with the largest equity market (the U.S.) has a positive loading.

[21] Tao and Yu (2012) show that, in a spatial setting, models of intertemporal choice often yield the non-linear restriction $\lambda = -\beta\rho$ in equation (1). With positive autocorrelation of the dependent variable ($\beta > 0$), and positive contemporaneous spatial spillovers ($\rho > 0$), the implication is that the lagged spatial spillover effect λ should be negative, as found here.

about local interactions is important for understanding the patterns of equity returns across countries and over time.

The estimated models do a good job at accounting for the cross-sectional dependence of equity returns highlighted in Table 2. For all three models, the CD test statistic shown at the bottom of Table 3 reveals little evidence of residual cross-sectional correlation. The exponent of cross-sectional dependence is in all cases under 0.5, likewise suggesting that the residuals exhibit no strong cross-sectional dependence.

Results using the advanced-country sample are shown in the bottom panel of Table 3. For the most part, the estimates follow the same sign and significance patterns of the full-country estimates. There are some differences, however. Credit growth now carries an insignificant coefficient. This result is consistent with the idea that among advanced countries financial frictions are less pervasive than in other countries, and therefore the interest rate suffices to summarize financial conditions. Also, the GDP growth parameter estimate is much larger than in the full sample, indicating that in advanced economies equity returns track growth fluctuations more closely than in the rest. Finally, the estimated spatial effects are consistently larger, in absolute value, than in the full sample, likely reflecting the deeper real and financial linkages among advanced countries relative to the rest. Still, the residuals seem to exhibit some traces of weak cross-sectional dependence, as the CD statistics border on statistical significance and the exponents of cross-sectional dependence lie around .7, well above the value of their full-sample counterparts.

Despite its simplicity, the model does a good job at tracking equity returns, as summarized by the R^2 shown in Table 3.[22]. The model accounts for close to 60 percent of the variation of the dependent variable in the full sample, and over 70 percent in the advanced-country sample, with the highest value corresponding in both cases to the bilateral trade specification of the weight matrix.

Table 4 further reports the R^2 by country for all the specifications estimated in Table 3. They range from over .8 (even .9 in the advanced-country sample) for a handful of advanced countries – France, Germany, the Netherlands, Sweden and the U.S. – to less than .1 for Colombia and .2 for Indonesia. In the full sample, the median R^2 is just under .7, and only 8 countries exhibit values under 0.5, while in the advanced-country subsample the median exceeds .75 and only two countries show values consistently below .5.

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

Table 3: Estimation results: alternative spatial weight matrices

	All countries		
Weight matrix	Trade	FDI	Distance
g_{t-1}	0.260	0.251	0.259
	(15.776)	(15.221)	(15.722)
GDP growth	0.301	0.298	0.338
	(2.892)	(2.831)	(3.235)
Δ Change in real interest rate	-0.663	-0.681	-0.685
	(-11.032)	(-11.281)	(-11.393)
Real credit growth	0.169	0.168	0.163
	(4.766)	(4.688)	(4.535)
Wg_t	0.442	0.234	0.230
	(15.283)	(8.111)	(9.493)
Wg_{t-1}	-0.178	-0.028	-0.112
	(-5.784)	(-1.081)	(-4.317)
Pesaran CD statistic	0.472	0.776	-0.521
(p-value)	(0.319)	(0.219)	(0.301)
Exponent of CSD	0.441	0.405	0.386
R^2	0.590	0.585	0.588
	Advanced countries		
g_{t-1}	0.254	0.283	0.280
	(12.009)	(13.577)	(13.360)
GDP growth	0.997	0.898	0.884
	(5.752)	(4.885)	(4.822)
Δ Change in real interest rate	-0.791	-0.503	-0.552
	(-3.611)	(-2.105)	(-2.320)
Real credit growth	-0.039	-0.035	-0.016
	(-0.696)	(-0.547)	(-0.251)
Wg_t	0.799	0.366	0.310
	(62.788)	(10.607)	(10.714)
Wg_{t-1}	-0.254	-0.251	-0.171
	(-8.937)	(-5.666)	(-4.612)
Pesaran CD statistic	1.694	1.857	1.13
(p-value)	(0.045)	0.032	(0.129)
Exponent of CSD	0.757	0.717	0.680
R^2	0.721	0.687	0.689

Notes: Bias-corrected QML estimates. For both country samples, the corresponding columns report results with trade, FDI and distance weight matrices. The dependent variable is the real stock return computed as the first difference of the log real equity price. GDP growth is the first difference of the log of real GDP, Δ Real interest rate is the first difference of the real interest rate, and Real credit growth is the first difference of the log of the real credit stock. 'Exponent of CSD' is the exponent of cross-sectional dependence. T-statistics in brackets and p-values in brackets for Pesaran CD statistic. The sample period covers 1995:1-2016:3.

4.2 Transmission of spatial impacts

The fundamental implication of the dynamic spatial model is that a shock in a particular country affects not only the equity returns of that country itself, but also the equity

Table 4: R^2 by country: alternative spatial weight matrices

	All countries				Advanced countries		
Country	Trade	FDI	Distance	Country	Trade	FDI	Distance
Australia	0.784	0.826	0.802	Australia	0.768	0.836	0.838
Austria	0.781	0.784	0.795	Austria	0.795	0.807	0.813
Belgium	0.706	0.675	0.722	Belgium	0.789	0.751	0.779
Canada	0.755	0.743	0.746	Canada	0.715	0.724	0.724
Denmark	0.795	0.796	0.808	Denmark	0.835	0.813	0.829
Finland	0.617	0.627	0.596	Finland	0.594	0.613	0.633
France	0.836	0.816	0.840	France	0.905	0.870	0.866
Germany	0.811	0.814	0.830	Germany	0.857	0.852	0.856
Greece	0.581	0.564	0.589	Greece	0.603	0.626	0.628
Hong Kong	0.519	0.529	0.545	Hong Kong	0.446	0.490	0.511
Iceland	0.604	0.584	0.583	Iceland	0.930	0.677	0.657
Ireland	0.708	0.694	0.712	Ireland	0.778	0.756	0.759
Israel	0.615	0.619	0.599	Israel	0.548	0.568	0.564
Italy	0.751	0.742	0.770	Italy	0.819	0.796	0.786
Japan	0.495	0.504	0.490	Japan	0.545	0.547	0.542
Korea	0.397	0.375	0.424	Korea	0.419	0.368	0.405
Netherlands	0.864	0.839	0.875	Netherlands	0.902	0.871	0.898
New Zealand	0.481	0.485	0.473	New Zealand	0.471	0.522	0.505
Norway	0.740	0.743	0.751	Portugal	0.745	0.728	0.698
Portugal	0.723	0.716	0.722	Norway	0.690	0.705	0.713
Spain	0.750	0.690	0.759	Spain	0.799	0.777	0.724
Sweden	0.840	0.848	0.827	Sweden	0.851	0.842	0.848
Switzerland	0.711	0.679	0.709	Switzerland	0.783	0.726	0.756
United Kingdom	0.809	0.764	0.803	United Kingdom	0.863	0.783	0.816
United States	0.806	0.837	0.837	United States	0.851	0.870	0.865
Argentina	0.659	0.650	0.629	**Median**	**0.783**	**0.751**	**0.756**
Brazil	0.610	0.624	0.611				
Chile	0.497	0.508	0.460				
China	0.331	0.352	0.327				
Colombia	0.033	0.036	0.031				
Czech Republic	0.699	0.697	0.678				
Indonesia	0.172	0.159	0.191				
Hungary	0.718	0.701	0.684				
Mexico	0.678	0.692	0.684				
Peru	0.567	0.566	0.543				
Poland	0.770	0.741	0.764				
Slovakia	0.240	0.334	0.279				
South Africa	0.631	0.641	0.595				
Turkey	0.556	0.533	0.552				
Slovenia	0.256	0.285	0.280				
Median	**0.688**	**0.677**	**0.681**				

returns of neighboring countries within the spatial system. In other words, incorporating the spatial interaction effects helps 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:

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

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 contemporaneous 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 β, λ 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.

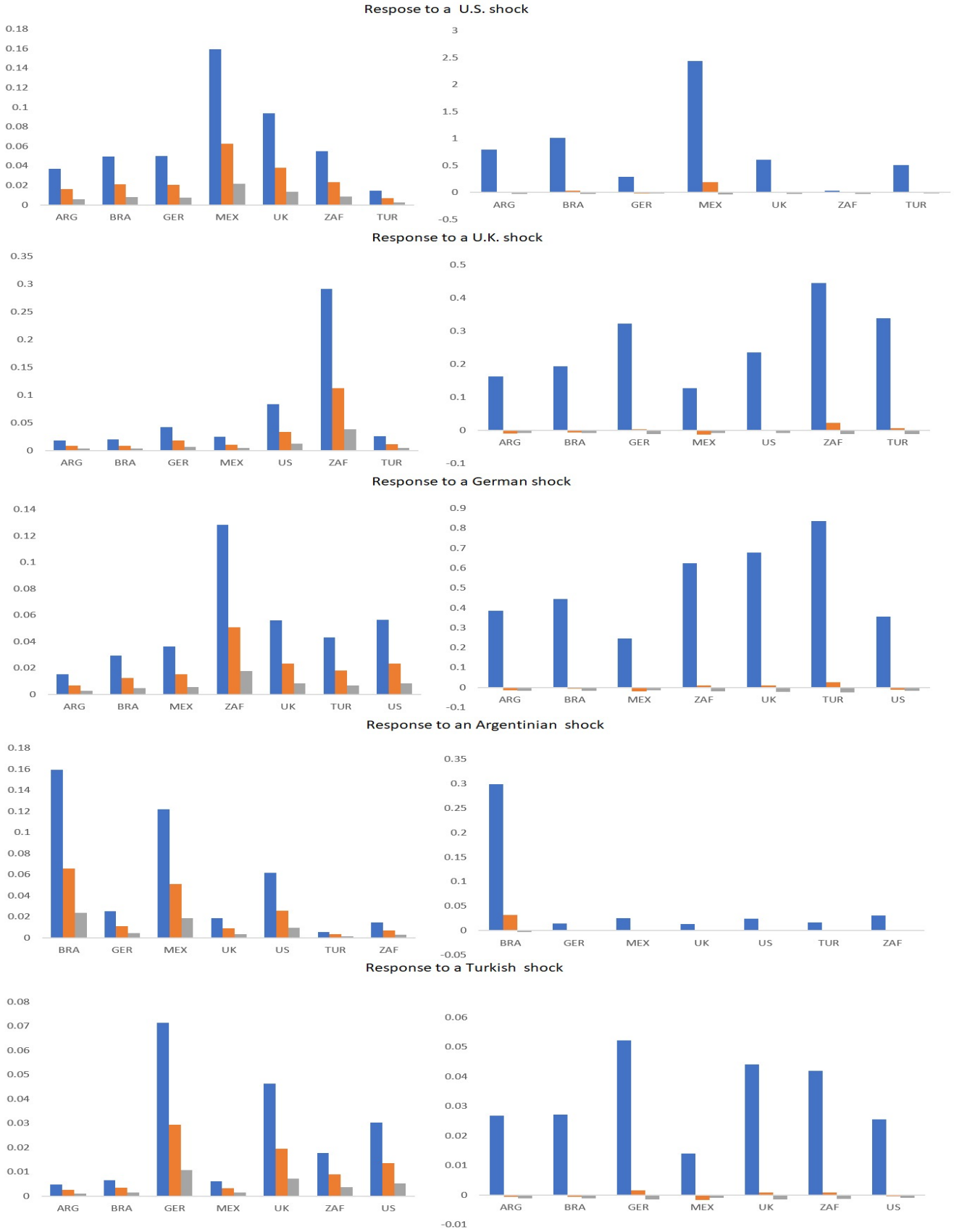
For illustration, Figure 3 reports the impact on selected countries of one-time shocks to equity returns in the U.S., the U.K., Germany, Argentina and Turkey. The graphs on the left side of the figure show the responses obtained with the full-sample estimates using the FDI spatial weight matrix, and the graphs on the right side show the responses when using instead the bilateral trade weight matrix. In each case, the graphs show the contemporaneous response to a unit shock to equity returns, and the dynamics over the subsequent three quarters.[23]

Two general features are worth noting. First, convergence is quite fast – after just four quarters, the impacts arising from the FDI linkages have virtually vanished; with the trade linkages, they vanish even faster. The reason is that the eigenvalues of the transition matrix turn out to be fairly small in absolute value (under 0.30), thus implying little persistence. Second, convergence is monotonic with the FDI matrix, but oscillating with the trade matrix. This is due to the larger negative estimate of the space-time lag in the latter specification.

The short-run effects are, in some cases, fairly substantial. For example, a unit shock to U.S. returns raises Mexican returns by 0.35 percent under the FDI specification of the weight matrix, and by a whopping 2.5 percent under the bilateral trade specification. In the latter case, U.S. shocks also have a larger impact on equity returns in Brazil and Argentina. Likewise, the impact of shocks to German stock returns on other countries is much larger under the bilateral trade specification of the weight matrix than under the FDI specification. The reason for these differences is twofold. First, the estimate of the contemporaneous spatial effect is almost twice as large under the former specification than under the latter. Second, the bilateral trade links of the countries shown with the U.S. and Germany are larger than their bilateral FDI links.

[23] The standard deviation of the return residuals is in both cases .07.

Figure 3: Dynamic spatial impacts



4.3 The common factor and the global financial cycle

An important element of the empirical model is the unobserved common factor driving equity returns around the world. Figure 4 depicts the common factor obtained from the model estimates using the bilateral trade matrix (column 1 of Table 3) along with the cross-country average equity returns, for both the advanced-country and the full samples. In both cases the common factor tracks average equity returns very closely. The estimated common factors are very similar across all the specifications shown in Table 3. For the full country sample, their pairwise correlations exceed .98; for the advanced-country subsample they exceed .74.

Rey (2013), Xu (2017) and Miranda-Agrippino and Rey (2018) likewise find a common factor behind asset prices worldwide, which they interpret as reflecting global investors' risk aversion – or the 'global financial cycle' (see also Barrot and Servén (2018) and Bekaert and Mehl (2017)). Consistent with this logic, Figure 5 plots the common factor estimated in column 1 of Table 3 and the VIX (shown using an inverted scale), commonly used as a summary measure of perceived aggregate risk. The figure depicts both the advanced-country and the full sample common factors. Both show a strong association with the VIX, as argued by the literature.

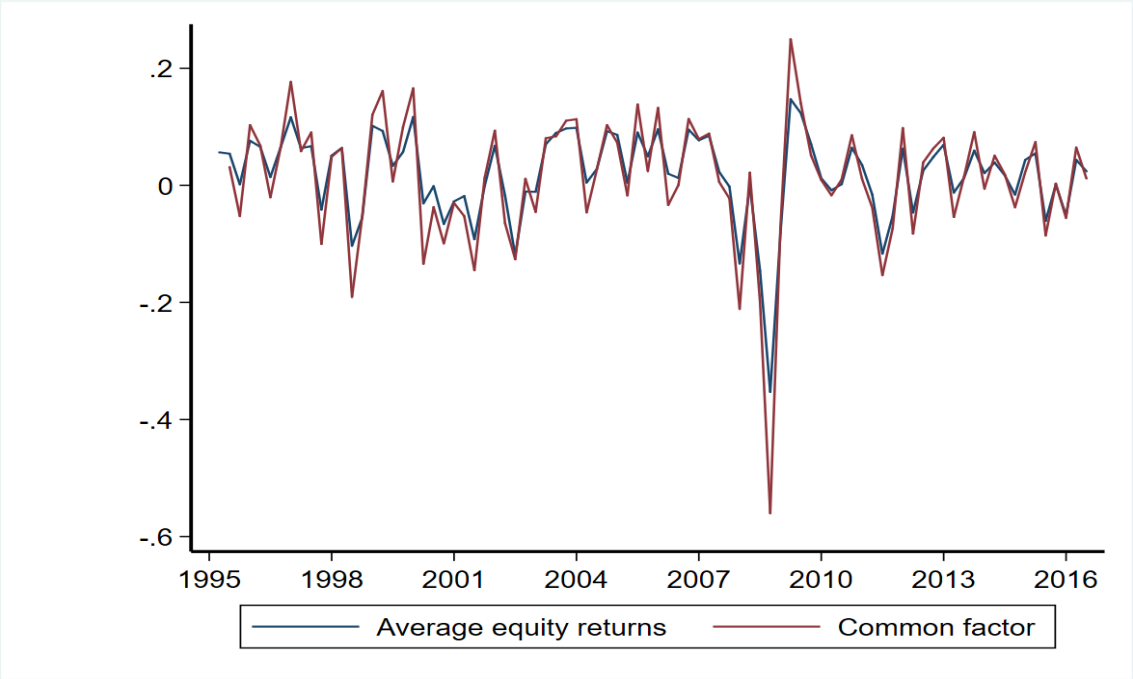
However, the world financial cycle may reflect other global forces besides risk – e.g., global interest rates, or the U.S. real exchange rate, owing to the dominant role of the U.S. dollar in financial transactions worldwide (see, e.g., Avdjiev et al (2017) and Bruno and Shin (2015)). To assess their contribution to the observed pattern of equity returns around the world, we examine the relationship between the estimated common factor and selected global variables.[24] In particular, we consider the VIX plus other measures of global risk – the Bank of America Merrill Lynch High Yield Spread (HYS), the Bank of America Below Options-Adjusted Spread (BOAS), Moody's Corporate Bond Yield Spread (MCOY), and the risk appetite and uncertainty indices of Bekaert, Engstrom, and Xu (2017). In addition, we consider the U.S. federal funds rate, expressed in real terms, as well as the first difference of the log of the U.S. real effective exchange rate, defined so that an increase represents an appreciation.

Table 5 reports the correlation of the common factors from the two country samples with each of these global variables. The correlations are negative in all cases, except for the U.S. short-term real interest rate, which exhibits a positive correlation with both global factors. All the correlations are statistically significant, except for that of the BOAS spread with the advanced-country factor. The strong negative correlation with the risk variables accords with the results of Miranda-Agrippino and Rey (2018) and Xu (2017), while the negative correlation with the real exchange rate confirms those of Bruno and Shin (2015), who argue that U.S. dollar real appreciation itself represents a global risk factor.

[24] For the exercises below we use the common factor obtained from the full-sample estimation using the bilateral trade matrix (column 1 of the top panel of Table 3). Results with the other factors are very similar.

Figure 4: Average equity returns and the common factor

(a) Advanced countries



(b) All countries

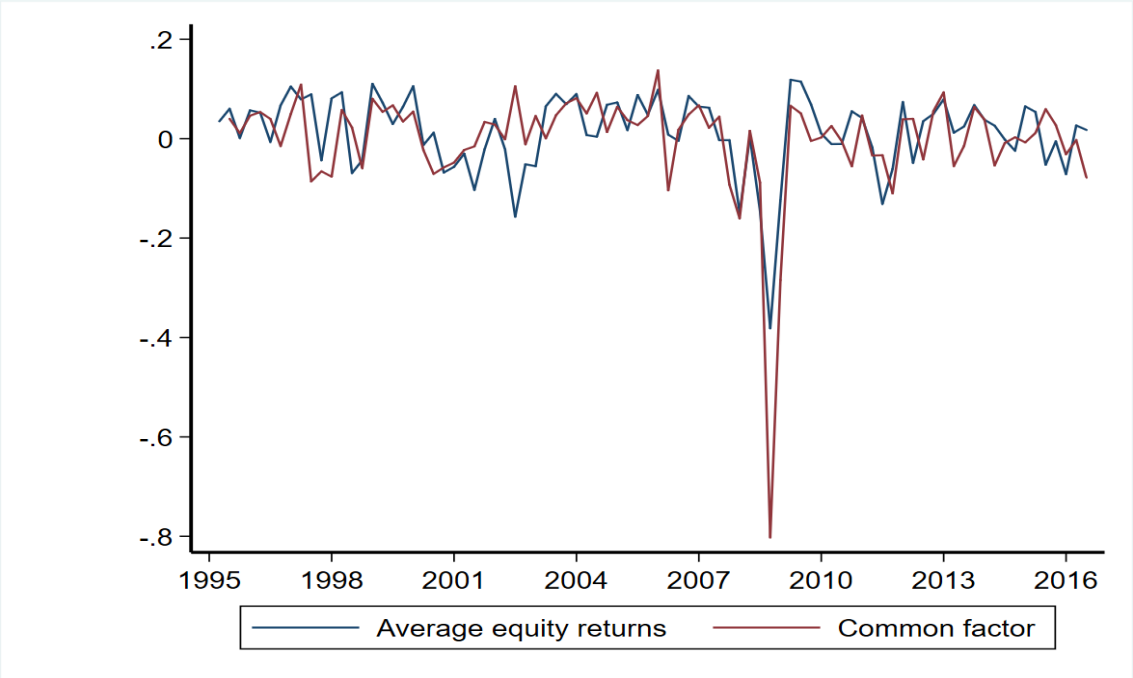


Figure 5: Common factors and the VIX

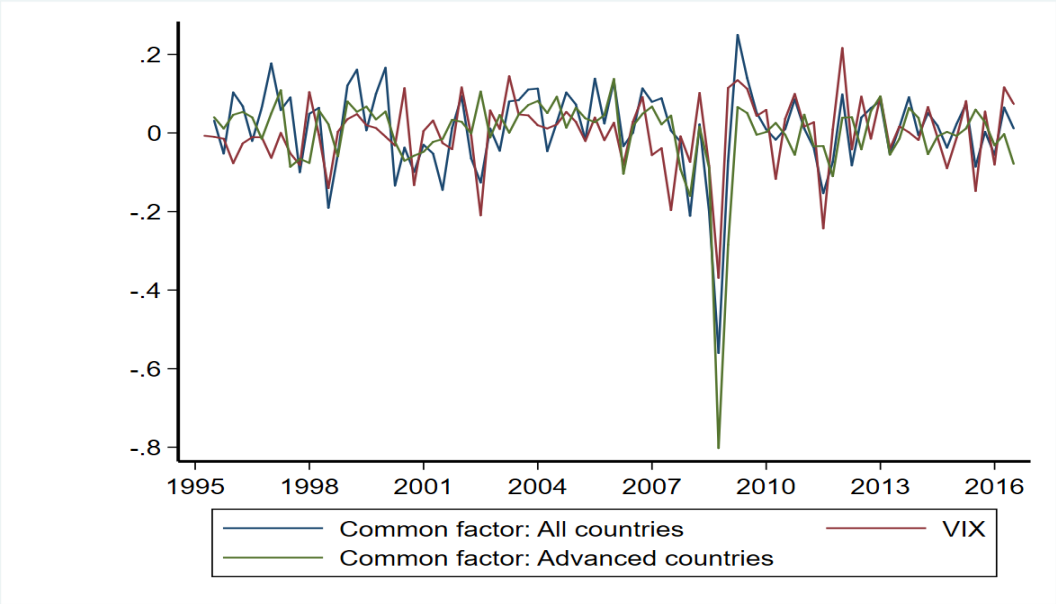


Table 5: Correlation of the common factor with global variables

	All countries	Advanced countries
Δ VIX	-0.638***	-0.332**
Δ Risk appetite	-0.503***	-0.579***
Δ Uncertainty	-0.526***	-0.612***
Δ Real Fed Funds Rate	0.401***	0.456***
Δ Real Exchange Rate	-0.448***	-0.368***
HYS	-0.448***	-0.588***
BOAS	-0.336**	-0.030
MOCY	-0.743***	-0.641***

Notes: The table shows the correlation of the estimated common factor of each sample from the first column of Table 3 with the global variables listed. Δ VIX is the first difference of the log VIX, Δ Real Fed Funds rate is the first difference of the Federal Funds rate in real terms, Δ Real exchange rate is the first difference of the log real effective exchange rate of the U.S. dollar, HYS is the Bank of America Merrill Lynch High Yield Spread, BOAS is the Bank of America Below Options-Adjusted Spread, MCOY is Moody's Corporate Bond Yield Spread. Δ Risk appetite is the first difference of risk appetite index, and Δ Uncertainty is the first difference of the uncertainty index, with both indices taken from Bekaert, Engstrom, and Xu (2017). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 6 reports regressions of the full-sample common factor on these global variables. We present regressions of the common factor on the VIX; the VIX plus the U.S. short-term real interest rate; these two variables plus the real exchange rate of the U.S.; and the full set of global variables considered. The regressions show that the VIX alone can account for over 40 percent of the variation of the common factor. Adding the U.S.

short-term real interest rate and real exchange rate raises the explanatory power of the regressions above 50 percent. Finally, adding the other risk measures further raises the R^2 to 66 percent, although several of them carry insignificant coefficients due to their high degree of collinearity.

Table 6: Covariates of the common factor

Variable	All countries			
	I	II	III	IV
Δ VIX	-0.021	-0.019	-0.017	-0.010
	(-4.230)	(-5.300)	(-5.740)	(-3.090)
Δ Real Fed Rate		0.219	0.217	0.133
		(3.000)	(3.110)	(2.34)
Δ Real Exchange rate			-0.030	-0.020
			(-2.910)	(-2.180)
Δ Risk appetite				0.012
				(-0.160)
HYS				0.001
				(0.200)
BOAS				-0.010
				(-1.340)
MCOY				-0.335
				(-3.380)
R^2	0.407	0.492	0.539	0.666

Notes: The dependent variable is the common factor from the full sample estimates in the first column of Table 3. Δ VIX is the first difference of the log VIX, Δ Real Fed Funds rate is the first difference of the real funds rate, Δ Real exchange rate is the first difference of the log real effective exchange rate of the U.S. dollar, HYS is the Bank of America Merrill Lynch High Yield Spread, BOAS is the Bank of America Below Options-Adjusted Spread, MCOY is Moody's Corporate Bond Yield Spread, Δ Risk appetite is the first difference of the risk appetite index. T-statistics in brackets computed with heteroscedasticity-consistent standard errors. The regressions include a constant.

4.4 The exposure to global financial shocks

Overall, the results in Table 6 support the view that the common factor driving equity returns across the world can be interpreted as a summary representation of global financial conditions. This raises the question of what determines countries' exposure to them – or, in other words, the sensitivity of their asset prices to global shocks. This is a first-order policy question that has attracted increased attention following the global financial crisis.

In our model, the sensitivity of each country's equity returns to the common shocks is given by its respective factor loading. The estimated loadings (shown in Table A4 in the Appendix) are very similar across the three specifications in Table 3: in the full country sample, their pairwise correlations exceed .98, while for the advanced-country sample the correlation exceeds .86. However, the loadings display considerable variation across countries. In the full sample they are all positive, except for three emerging countries (Colombia, Indonesia and Slovakia) that exhibit very small negative values. On

average, they are also larger among advanced countries than among emerging countries. The largest values belong to major emerging markets – Argentina, Turkey – and small open advanced economies – Iceland, Greece. In the advanced-country sample,Iceland consistently exhibits the largest loading, especially when using the trade-based matrix to estimate the model.

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.[25]

Specifically, the variables we consider include capital account openness, trade openness, financial depth, stock market capitalization and the exchange rate regime. In particular, the latter variable has been at the center of the policy debate following the claim by Rey (2013) that the global financial cycle renders virtually irrelevant any distinctions between exchange rate regimes regarding their ability to shelter the economy from external financial disturbances.[26]

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 21-year time sample. Over this time span the explanatory variables have surely undergone major changes, and this should tend to obscure their relationship with the loadings. Hence the regressions probably understate the strength of that relationship, and should be viewed with some caution.

Table 7: Covariates of the factor loadings

Covariates	I	II	III	IV	V	VI
Financial openness	0.130					-0.022
	(11.30)					(-0.490)
Trade openness		0.034				0.042
		(2.56)				(6.010)
Exchange rate arrangement			-0.032			-0.023
			(-3.367)			(-1.66)
Stock market capitalization				0.118		-0.030
				(3.810)		(-1.370)
Domestic credit (% of GDP)					0.118	0.044
					(7.330)	(1.100)
R^2	0.848	0.105	0.395	0.531	0.760	0.923

The table reports regressions on the variables shown of the factor loadings from the full sample estimates in the first column of Table 3. An increase in the value of the exchange rate regime variable denotes a more flexible regime. Trade openness is measured in logs. T-statistics in brackets computed with heteroscedasticity-consistent standard errors. The regressions include a constant. The sample comprises 25 observations.

Table 7 reports the regression results using the factor loadings as dependent variable. The univariate regressions in the first five columns show that the loadings increase

[25]Because the loadings exhibit little variation across the three estimated models in the top half of Table 3, we only report exercises using the loadings from the model that employs the trade weight matrix.

[26]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.

significantly with financial and trade openness, the size of the stock market, and domestic financial depth. In contrast, they decrease with a more flexible exchange rate regime. The last column of Table 7 shows that when all variables are jointly considered they can account for over 90 percent of the variation of the factor loadings. However, because of strong collinearity among the variables, only trade openness and the exchange rate regime remain individually significant. One implication is that, in spite of the worldwide reach of the global financial cycle, the choice of exchange regime continues to matter for the exposure of domestic asset prices to international shocks.

4.5 Sensitivity analysis

Finally, we examine the sensitivity of our main results to alternative ways of modeling the cross-country dependence of equity returns. 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.[27]

The results are shown in Table 8. 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 three columns allow for spatial effects but rule out common factors (i.e., $\Psi = \mathbf{0}$); each of these columns corresponds to one specification of the spatial weight matrix. The top panel of Table 8 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 8 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 GDP growth parameter estimate doubles relative to that in Table 3; most of the other coefficient estimates exhibit large changes too. Also, in the advanced country sample the coefficient estimate of the real interest rate becomes insignificant. 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 is quite poor, as it accounts for less than 20 percent of the variation of the dependent variable.

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

Table 8: Estimation results: alternative specifications of cross-sectional dependence

	All countries				
			Spatial only		
	None	Factor only	Trade	FDI	Distance
g_{t-1}	0.323	0.256	0.273	0.263	0.272
	(15.106)	(15.506)	(16.806)	(16.061)	(16.671)
GDP growth	0.577	0.343	0.302	0.261	0.394
	(4.044)	(3.232)	(2.785)	(2.292)	(3.556)
Δ Real interest rate	-0.917	-0.680	-0.752	-0.776	-0.786
	(-11.104)	(-11.193)	(-11.997)	(-11.806)	(-12.274)
Real credit growth	0.173	0.162	0.143	0.120	0.117
	(4.009)	(4.443)	(4.357)	(3.469)	(3.487)
Wg_t			0.799	0.660	0.626
			(71.970)	(37.633)	(42.764)
Wg_{t-1}			-0.231	-0.125	-0.160
			(-9.765)	(-5.411)	(-7.561)
Pesaran CD statistic	126.681	4.867	11.745	27.812	26.02
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exponent of CSD	0.982	0.617	0.841	0.907	0.876
R^2	0.144	0.576	0.512	0.462	0.495
Factor	No	Yes	No	No	No
Spatial	No	No	Yes	Yes	Yes
	Advanced countries				
g_{t-1}	0.344	0.283	0.305	0.305	0.292
	(10.788)	(13.498)	(14.480)	(14.488)	(13.705)
GDP growth	1.876	0.990	1.027	1.010	1.074
	(6.725)	(5.305)	(5.578)	(5.490)	(5.701)
Δ Real interest rate	-0.376	-0.368	-0.441	-0.353	-0.382
	(-1.109)	(-1.506)	(-1.969)	(-1.577)	(-1.671)
Real credit growth	0.083	-0.025	0.003	-0.008	0.017
	(1.073)	(-0.392)	(0.054)	(-0.156)	(0.328)
Wg_t			0.832	0.784	0.730
			(80.199)	(54.610)	(48.889)
Wg_{t-1}			-0.243	-0.242	-0.187
			(-8.509)	(-8.976)	(-6.899)
Pesaran CD statistic	101.718	9.313	4.393	6.727	13.007
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exponent of CSD	1.002	0.799	0.924	0.846	0.897
R^2	0.156	0.673	0.643	0.646	0.631
Factor	No	Yes	No	No	No
Spatial	No	No	Yes	Yes	Yes

Notes: Bias-corrected QML estimates. The dependent variable is the real stock return computed as the first difference of the log real equity price. GDP growth is the first difference of the log of real GDP, Δ Real interest rate is the first difference of the real interest rate, and Real credit growth is the first difference of the log of the real credit stock. T-statistics in brackets. The sample period covers 1995:1-2016:3.

The second column of Table 8 adds a common factor but omits spatial effects. The

parameter estimates are now much closer to those in Table 3, with the only exception of the real interest rate in the advanced-country sample, whose coefficient remains small (in absolute value) and insignificant. The CD statistic continues to show evidence of cross-sectional dependence, but its value falls sharply relative to that in the first column. In turn, the exponent of cross-sectional dependence also declines well below 1. Together, these statistics suggest that the common factor succeeds in taking account of the strongest dependence in the data, but still leaves considerable (weak) dependence in the residuals. Lastly, the fit of the model shows a considerable improvement relative to the preceding column, with the R^2 rising threefold.

The last three columns of Table 8 report estimates including spatial effects, for each of the three versions of the spatial weight matrix we consider, but excluding the common factor. The spatial effects are strongly significant – in fact, both their magnitude and their significance appear substantially overstated relative to the results shown in Table 3. This is particularly the case for the spatial lag, whose parameter estimate is much larger than in Table 3; its massive t-statistic hints at residual dependence. The values of the other parameter estimates lie in most cases between those in the first column and those in the applicable column of Table 3. In turn, the cross-sectional dependence statistics show in general lower values than in the first column of Table 8, but higher than in the factor-only model of the second column. In particular, the exponent of cross-sectional dependence is fairly close to that in the first column, suggesting that the spatial effects do little to ameliorate the strong dependence in the data. Lastly, the overall fit of the model, as measured by R^2, improves substantially relative to column I with the addition of the spatial variables. However, it is worse than that of the factor-only model.

Overall, comparison of Tables 3 and 8 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.

Table A5 in the appendix reports the individual-country R^2 for each of the estimated model specifications in Table 8. On the whole, the pattern is the same as in Table 8: the fit is very poor (R^2 of .3 or lower) when cross-sectional dependence is ignored, and improves substantially when either the common factor or spatial dependence is taken into account – although in both cases the fit is unsurprisingly poorer than that obtained when both features are jointly included, as shown in Table 4.

Finally, Table 9 reports further robustness checks on the specification of the empirical model. To save space, only results using the bilateral trade weight matrix are reported; however, results with the other matrices are not very different. The first column adds to the baseline specification in column 1 of Table 3 a spatial error term. The result is a deterioration in the empirical performance of the model. In the full sample, the spatial error is insignificant, and the rest of the estimates show little change relative to the baseline. In the advanced-country sample, the parameter estimates of the fundamental variables all become insignificant, and the residuals show strong symptoms of dependence.

The second column employs two factors in the estimation, rather than the single factor used in the baseline specification following the verdict of the information criteria. The main consequence is that the estimates of the spatial effects become smaller than in the baseline, as more of the cross-sectional dependence is taken up by the factors. This

is especially visible in the advanced-country subsample; also, the evidence of residual dependence weakens. The overall fit of the model improves relative to that in Table 3.

Table 9: Additional robustness checks

	All countries		
	Spatial error	Two factors	Demeaning
g_{t-1}	0.260	0.270	0.270
	(15.727)	(16.204)	(16.806)
GDP growth	0.29	0.31	0.30
	(2.749)	(3.015)	(2.785)
Δ Real interest rate	-0.66	-0.64	-0.75
	(-11.011)	(-10.828)	(-11.997)
Real credit growth	0.17	0.15	0.14
	(4.817)	(4.315)	(4.357)
Wg_t	0.390	0.150	0.800
	(1.199)	(3.983)	(71.969)
Wg_{t-1}	-0.160	-0.090	-0.230
	(-2.276)	(-2.233)	(-9.765)
Spatial error	0.110		
	(0.321)		
Pesaran CD statistic	1.660	0.105	2.551
(p-value)	(0.048)	(0.458)	(0.005)
Exponent of CSD	0.505	0.444	0.719
R^2	0.589	0.643	0.524
	Advanced countries		
g_{t-1}	0.305	0.232	0.305
	(14.283)	(10.981)	(14.481)
GDP growth	0.246	1.223	1.027
	(1.349)	(7.142)	(5.578)
Δ Real interest rate	0.005	-0.646	-0.441
	(0.022)	(-2.684)	(-1.969)
Real credit growth	0.005	-0.074	0.003
	(0.086)	(-1.207)	(0.054)
Wg_t	0.023	0.532	0.832
	(0.082)	(17.438)	(80.199)
Wg_{t-1}	-0.313	-0.082	-0.243
	(-5.701)	(-1.867)	(-8.509)
Spatial error	0.701		
	(2.799)		
Pesaran CD statistic	12.788	-0.594	-0.261
(p-value)	(0.000)	(0.276)	(0.397)
Exponent of CSD	0.882	0.661	0.738
R^2	0.702	0.760	0.648

Notes: Bias-corrected QML estimates. The dependent variable is the real stock return computed as the first difference of the log real equity price. GDP growth is the first difference of the log of real GDP, Δ Real interest rate is the first difference of the real interest rate, and Real credit growth is the first difference of the log of the real credit stock. 'Exponent of CSD' is the exponent of cross-sectional dependence. T-statistics in brackets and P-values in brackets for Pesaran CD statistic. The sample period covers 1995:1-2016:3.

The last column of Table 9 attempts to address the strong dependence of the returns by cross-sectional de-meaning of the data prior to estimation, instead of adding common factors in the regression specification. This can be viewed as equivalent to a factor model imposing the implicit restriction that the loadings be constant across countries. The parameter estimates on the fundamental variables show some changes relative to Table 3 – particularly in the case of the real interest rate in the advanced-country sample, whose coefficient declines by half. In addition, the spatial effects appear overstated, especially in the full sample, and the huge t-statistic on the spatial lag hints at misspecification.

5 Conclusion

Equity returns display strong international comovement, especially across advanced countries. Existing empirical literature has modeled it as reflecting either localized real and/or financial linkages across countries, 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 comovement of equity returns in a setting that allows for both spatial dependence and latent common factors, using quarterly equity price data over the years 1995 to 2016 for 40 advanced and emerging countries.

In the paper's framework, real equity returns are driven by three observable variables proxying for growth of the present value of anticipated dividends: the growth rates of GDP and real credit, and the change in the real interest rate. These variables are augmented with latent common factors and spatial effects accruing through equity prices themselves.

We estimate the model using a bias-corrected quasi-maximum likelihood procedure recently developed by Shi and Lee (2017), alternatively considering all 40 sample countries, or a subsample of 25 advanced economies. To capture the interactions among countries, we employ alternative spatial weight matrices based on bilateral trade, bilateral FDI stocks, and geographic distance. To determine the number of latent common factors driving equity returns, we use a variety of information criteria. On the whole, they indicate the presence of a single factor for both country samples considered.

Estimation results reveal that, in accordance with prior expectations, real equity returns are significantly positively related to real GDP growth, and negatively related to changes in the real interest rate. In the advanced-country subsample, real credit growth has no significant effect on equity returns. However, in the full sample, which includes countries with less-developed financial markets, credit growth carries a positive and strongly significant coefficient. In addition, equity returns display significant inertia in both samples.

The results show little variation across the three alternative specifications of the spatial weight matrix. They also provide strong evidence of spatial effects. The contemporaneous spatial lag coefficient is consistently positive and significant, while the spatial-time lag carries a negative coefficient that is significant in most specifications. The significant spatial effects imply that local interactions are important to understand the international comovement of equity returns.

In turn, the estimated common factor is strongly positively correlated with real

equity returns, and strongly negatively correlated with market indicators of aggregate risk. Overall, the common factor can be interpreted as summarizing the 'global financial cycle' stressed by Rey (2013) and Miranda-Agrippino and Rey (2018).

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 equity returns is bigger in countries that exhibit higher trade openness and whose exchange rate regimes exhibit less flexibility. The latter result in particular suggests that, notwithstanding the worldwide reach of the global financial cycle, the choice of exchange rate regime still matters for countries' exposure to global financial shocks – which echoes the recent findings of Bekaert and Mehl (2017) and Barrot and Servén (2018).

Despite its simplicity, the empirical model does a good job at explaining observed equity returns. In the baseline specification, it accounts for close to 60 percent of the variance of equity returns in the full country sample, and 70 percent in the advanced-country subsample.

Our empirical exercises underscore the importance of properly taking into account cross-sectional dependence. Ignoring it, by omitting both common factors and spatial effects, causes major distortions in the parameter estimates, leading in particular to a gross overstatement of the procyclical behavior of equity returns. It also results in a abysmal deterioration of the model's explanatory power. Adding the common factor, while still omitting spatial effects, helps correct these problems, but leaves evidence of residual (weak) dependence. In turn, allowing for spatial effects, while omitting the common factor, also improves the fit considerably, but leads to overstated spatial effects and strong residual dependence. Overall, these results confirm the need to account for cross-sectional dependence, both strong and weak, in empirical modeling of equity returns across countries.

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Appendix A: Additional tables

Table A1: List of countries

Advanced countries	All countries
1. Australia	1. Australia
2. Austria	2. Austria
3. Belgium	3. Belgium
4. Canada	4. Canada
5. Denmark	5. Denmark
6. Finland	6. Finland
7. France	7. France
8. Germany	8. Germany
9. Greece	9. Greece
10. Hong Kong	10. Hong Kong
11. Iceland	11. Iceland
12. Ireland	12. Ireland
13. Israel	13. Israel
14. Italy	14. Italy
15. Japan	15. Japan
16. Korea	16. Korea
17. Netherlands	17. Netherlands
18. New Zealand	18. New Zealand
19. Norway	19. Norway
20. Portugal	20. Portugal
21. Spain	21. Spain
22. Sweden	22. Sweden
23. Switzerland	23. Switzerland
24. United Kingdom	24. United Kingdom
25. United States	25. United States
	26. Argentina
	27. Brazil
	28. Chile
	29. China
	30. Colombia
	31. Czech Republic
	32. Indonesia
	33. Hungary
	34. Mexico
	35. Peru
	36. Poland
	37. Slovakia
	38. Slovenia
	39. South Africa
	40. Turkey

Table A2: Data sources and definition

Variable	**Definition**	**Source**
Equity returns	The first difference of log real equity equity price indices	OECD, IFS, Investing.com
GDP growth	The first difference of log real GDP	OECD, IFS
Interest rates	The first difference of real interest rates	IFS, BIS
Credit growth	The firts difference of real credit stock	BIS, Datastream, FRED
VIX	The Chicago Board Options Exchange (CBOE) Volatility index	FRED
HYS	BofA Merrill Lynch U.S. High Yield Spread	FRED
BOAS	BofA Merrill Lynch U.S. Options-Adjusted Spread	FRED
MCOY	Moody's Seasoned Corporate Bond Yield	FRED
Federal Funds rate	Real Federal Funds Rate	FRED
Effective exchange rate	The U.S. real exchange rate	FRED
Bilateral FDI	Stock of bilateral FDI	OECD
Bilateral trade	Bilateral trade flow	IFS, CEPII
Domestic credit	Domestic credit to private sector as % of GDP	WDI, WB
Financial openness	Chinn-Ito index of Capital account liberalization	Chinn-Ito
Exchange rate regime	Exchange rate	Ghosh, Ostry, Kapan and Qureshi (2015)
Stock market capitalization	Total value of listed shares as % of GDP	WDI
Latitude and longitude coordinates	Latitude and longitude coordinates of country capitals	CEPII
Risk aversion and uncertainty	Risk aversion and uncertainty index	Bekaert, Engstrom, and Xu (2017)

Table A3: Descriptive statistics of equity returns

	Mean	Std.dev	Min.	Max.		Mean	Std.dev	Min.	Max.
1. Australia	0.013	0.057	-0.248	0.121	33. Hungary	0.036	0.124	-0.438	0.358
2. Austria	0.009	0.105	-0.606	0.189	34. Mexico	0.038	0.094	-0.259	0.288
3. Belgium	0.014	0.083	-0.370	0.183	35. Peru	0.031	0.151	-0.577	0.468
4. Canada	0.015	0.077	-0.372	0.160	36. Poland	0.022	0.106	-0.335	0.295
5. Denmark	0.024	0.085	-0.394	0.154	37. Slovakia	0.005	0.096	-0.227	0.349
6. Finland	0.018	0.126	-0.348	0.416	38. Slovenia	0.011	0.112	-0.436	0.268
7. France	0.012	0.083	-0.270	0.192	39. South Africa	0.026	0.078	-0.261	0.162
8. Germany	0.012	0.092	-0.315	0.230	40. Turkey	0.065	0.184	-0.383	0.643
9. Greece	-0.005	0.152	-0.479	0.463					
10. Hong Kong	0.012	0.115	-0.384	0.282					
11. Iceland	0.013	0.189	-1.246	0.231					
12. Ireland	0.014	0.101	-0.492	0.207					
13. Israel	0.025	0.090	-0.358	0.264					
14. Italy	0.005	0.095	-0.304	0.253					
15. Japan	-0.001	0.089	-0.355	0.224					
16. Korea	0.009	0.123	-0.390	0.320					
17. Netherlands	0.010	0.092	-0.419	0.163					
18. New Zealand	0.008	0.051	-0.177	0.101					
19. Norway	0.024	0.109	-0.509	0.231					
20. Portugal	0.012	0.096	-0.279	0.242					
21. Spain	0.013	0.089	-0.234	0.219					
22. Sweden	0.019	0.094	-0.289	0.292					
23. Switzerland	0.014	0.072	-0.211	0.158					
24. United Kingdom	0.009	0.059	-0.229	0.106					
25. United States	0.016	0.069	-0.363	0.125					
26. Argentina	0.044	0.167	-0.540	0.567					
27. Brazil	0.033	0.129	-0.391	0.299					
28. Chile	0.016	0.069	-0.188	0.197					
29. China	0.019	0.139	-0.320	0.292					
30. Colombia	0.032	0.102	-0.195	0.281					
31. Czech Republic	0.007	0.108	-0.469	0.247					
32. Indonesia	0.023	0.125	-0.492	0.371					

Notes: Equity returns are measured as the first difference of log real equity price indices. The sample period covers 1995:1-2016:3.

Table A4: Estimated factor loadings, by country

	All countries				Advanced countries		
Country	Trade	FDI	Distance	Country	Trade	FDI	Distance
Australia	0.074	0.102	0.095	Australia	0.014	0.140	0.128
Austria	0.189	0.191	0.193	Austria	0.240	0.250	0.249
Belgium	0.087	0.114	0.119	Belgium	0.054	0.151	0.153
Canada	0.125	0.131	0.137	Canada	0.049	0.156	0.159
Denmark	0.120	0.130	0.138	Denmark	0.102	0.153	0.178
Finland	0.199	0.187	0.190	Finland	0.132	0.239	0.249
France	0.128	0.140	0.151	France	0.039	0.186	0.192
Germany	0.150	0.157	0.164	Germany	0.062	0.206	0.206
Greece	0.223	0.225	0.222	Greece	0.305	0.312	0.305
Hong Kong	0.181	0.183	0.180	Hong Kong	0.065	0.212	0.210
Iceland	0.302	0.246	0.265	Iceland	0.845	0.428	0.403
Ireland	0.134	0.141	0.144	Ireland	0.155	0.194	0.194
Israel	0.137	0.128	0.124	Israel	0.072	0.161	0.149
Italy	0.141	0.156	0.159	Italy	0.049	0.198	0.200
Japan	0.097	0.113	0.112	Japan	0.119	0.160	0.153
Korea	0.130	0.145	0.135	Korea	-0.029	0.125	0.137
Netherlands	0.152	0.161	0.171	Netherlands	0.095	0.211	0.222
New Zealand	0.019	0.042	0.042	New Zealand	-0.040	0.047	0.046
Norway	0.201	0.199	0.202	Portugal	0.042	0.179	0.174
Portugal	0.129	0.151	0.148	Norway	0.159	0.239	0.254
Spain	0.122	0.133	0.147	Spain	0.021	0.178	0.171
Sweden	0.151	0.156	0.159	Sweden	0.036	0.182	0.194
Switzerland	0.062	0.089	0.098	Switzerland	-0.010	0.123	0.122
United Kingdom	0.054	0.084	0.088	United Kingdom	-0.057	0.090	0.096
United States	0.093	0.110	0.118	United States	0.047	0.143	0.144
Argentina	0.274	0.264	0.253	**Median**	**0.054**	**0.179**	**0.178**
Brazil	0.217	0.222	0.208				
Chile	0.045	0.067	0.071				
China	0.126	0.138	0.124				
Colombia	-0.094	-0.055	-0.042				
Czech Republic	0.190	0.192	0.179				
Indonesia	-0.084	-0.026	-0.035				
Hungary	0.225	0.226	0.229				
Mexico	0.144	0.149	0.142				
Peru	0.242	0.246	0.210				
Poland	0.187	0.184	0.197				
Slovakia	-0.076	-0.034	-0.018				
South Africa	0.098	0.115	0.108				
Turkey	0.279	0.229	0.252				
Slovenia	0.048	0.065	0.083				
Median	**0.132**	**0.143**	**0.145**				

Table A5: R^2 by country: alternative specification of cross-sectional dependence

Country	None	Factor only	Trade	FDI	Distance
Australia	0.098	0.792	0.750	0.764	0.718
Austria	0.106	0.796	0.715	0.651	0.725
Belgium	0.186	0.664	0.775	0.692	0.816
Canada	0.056	0.724	0.715	0.716	0.664
Denmark	0.211	0.784	0.814	0.774	0.844
Finland	0.112	0.597	0.592	0.638	0.493
France	0.134	0.794	0.913	0.855	0.852
Germany	0.140	0.805	0.858	0.813	0.837
Greece	0.191	0.583	0.568	0.396	0.567
Hong Kong	0.017	0.493	0.367	0.278	0.516
Iceland	0.302	0.596	0.569	0.608	0.533
Ireland	0.291	0.682	0.759	0.727	0.751
Israel	0.068	0.605	0.535	0.577	0.489
Italy	0.124	0.727	0.818	0.756	0.821
Japan	0.118	0.493	0.492	0.457	0.480
Korea	0.088	0.372	0.374	0.280	0.496
Netherlands	0.152	0.830	0.925	0.820	0.842
New Zealand	0.105	0.445	0.478	0.514	0.501
Norway	0.070	0.742	0.695	0.609	0.656
Portugal	0.187	0.694	0.755	0.724	0.745
Spain	0.126	0.714	0.799	0.604	0.779
Sweden	0.175	0.818	0.864	0.859	0.768
Switzerland	0.200	0.656	0.775	0.721	0.808
United Kingdom	0.104	0.739	0.849	0.777	0.828
United States	0.166	0.827	0.813	0.846	0.750
Argentina	0.215	0.629	0.578	0.443	0.460
Brazil	0.065	0.603	0.481	0.455	0.467
Chile	0.126	0.476	0.470	0.455	0.398
China	0.092	0.345	0.320	0.304	0.256
Colombia	0.019	0.020	0.007	0.018	0.008
Czech Republic	0.101	0.689	0.572	0.460	0.577
Indonesia	0.182	0.172	0.130	0.141	0.148
Hungary	0.113	0.697	0.620	0.506	0.422
Mexico	0.186	0.669	0.577	0.570	0.625
Peru	0.120	0.538	0.485	0.329	0.521
Poland	0.083	0.749	0.719	0.667	0.700
Slovakia	0.282	0.288	0.095	0.166	0.123
South Africa	0.120	0.638	0.594	0.596	0.440
Turkey	0.185	0.541	0.414	0.416	0.423
Slovenia	0.140	0.291	0.235	0.269	0.265
Median	**0.125**	**0.660**	**0.593**	**0.600**	**0.572**

Country	None	Factor only	Trade	FDI	Distance
Australia	0.121	0.792	0.774	0.745	0.805
Austria	0.125	0.821	0.703	0.712	0.710
Belgium	0.216	0.746	0.789	0.744	0.809
Canada	0.064	0.697	0.696	0.711	0.676
Denmark	0.205	0.830	0.822	0.802	0.804
Finland	0.136	0.612	0.587	0.604	0.626
France	0.147	0.852	0.917	0.903	0.854
Germany	0.156	0.854	0.875	0.867	0.863
Greece	0.192	0.630	0.554	0.565	0.563
Hong Kong	0.030	0.441	0.421	0.472	0.507
Iceland	0.302	0.644	0.576	0.613	0.579
Ireland	0.311	0.751	0.765	0.756	0.750
Israel	0.072	0.570	0.515	0.515	0.514
Italy	0.135	0.783	0.828	0.824	0.794
Japan	0.133	0.535	0.513	0.517	0.409
Korea	0.117	0.352	0.398	0.351	0.427
Netherlands	0.158	0.880	0.918	0.871	0.865
New Zealand	0.127	0.414	0.491	0.556	0.539
Portugal	0.209	0.703	0.747	0.757	0.704
Norway	0.062	0.724	0.664	0.635	0.567
Spain	0.126	0.740	0.792	0.805	0.684
Sweden	0.190	0.816	0.846	0.862	0.862
Switzerland	0.237	0.739	0.795	0.772	0.810
United Kingdom	0.145	0.761	0.851	0.799	0.827
United States	0.209	0.857	0.853	0.876	0.806
Median	**0.145**	**0.740**	**0.765**	**0.745**	**0.710**

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 η_0. Under appropriate assumptions, using the perturbation theory of linear operators the limiting distribution of $\hat{\eta}$ around η_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 Σ is given in Shi and Lee (2017).

Equation (A1) indicates that the limiting distribution of $\hat{\eta}$ may deviate from η_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

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