Export diversification and economic development: A dynamic spatial data analysis

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Abstract

This paper contributes to the empirical literature on the relationship between "export variety" (export diversification) and economic development by relaxing the assumption of cross-country independence and allowing for spatial diffusion of shocks in observed and unobserved factors. Export variety is measured for a balanced panel of 114 countries (1992–2012) using very detailed information on their exports (HS 6-digit product level). The estimation results of a dynamic spatial panel data model confirm the relevance of spatial network effects in export diversification: indirect effects (spatial spillovers) strongly reinforce direct effects, while spatial proximity to large countries accelerates the diversification process. In about 10 years the whole space–time diffusion of the diversification shock is widely completed. We reveal that the long-run spillover impact from European countries is much higher than from other countries such as the United States, Japan, or the BRICS (Brazil, Russia, India, China, and South Africa).

1 | INTRODUCTION

Diversification paths during the process of economic development is a topic that has attracted the attention of many economists (Imbs & Wacziarg, 2003; Koren & Tenreyro, 2007; Klinger & Lederman, 2006; Cadot, Carrère, & Strauss-Kahn, 2011, 2013; Minondo, 2011; Parteka & Tamberi, 2013a,b; Mau, 2016). Diversifying exports is one of the main strategies that a country may follow to reduce uncertainty (Di Giovanni & Levchenko, 2011; Koren & Tenreyro, 2007, 2013). This ability is especially crucial in the case of developing countries, which are typically characterized by low diversification of their economic structure (Amurgo-Pacheco & Pierola, 2008; Carrère & Strauss-Kahn, 2014). From a theoretical point of view, increasing the variety of goods produced is expected to exert a positive impact on productivity and economic growth as shown, for instance, in models of "expanding product variety" (Barro & Sala-i-Martin, 2004, pp. 285–315; Grossman & Helpman, 1991a, pp. 43–83, 1991b). Consequently, it is not surprising that the topic of evolving diversification along the path of growth has been widely explored, mainly empirically.[1]

Discussion so far has mainly regarded the relationship between GDP per capita and levels of diversification of economic activity. Some authors (Imbs & Wacziarg, 2003; Koren & Tenreyro, 2007; Klinger & Lederman, 2006; Cadot et al., 2011) argued that in the first stage, at low levels of income, growth goes in line with an increase in the level of diversification; however, once countries reach a certain level of income, further growth is accompanied by re-concentration.[2] Several scholars (De Benedictis, Gallegati, & Tamberi, 2008, 2009; Parteka, 2010; Parteka & Tamberi, 2013a,b), however, show skepticism about the robustness of these patterns, correcting conventional, absolute measures of product diversity and find a nonlinear but monotonically decreasing trend reflecting progressive relative de-specialization along the path of economic growth. More recently, Mau (2016) has stressed that the above-cited nonmonotonic hump-shaped pattern is mainly due to an omitted log-transformation of the income variable, as well as sample selection bias and lack of control variables.

By focusing on measurement issues (absolute vs. relative measures of export diversification),[3] the functional form of the model (linear vs. quadratic) and other model specification issues (log-transformation, dynamic specification, and so on), the empirical literature has totally neglected another important source of bias, namely the existence of cross-country (or spatial) dependence in the data-generating process. Indeed, all the aforementioned studies analyze the relationship between trade diversification and economic development under the (implicit) assumption of spatial independence.[4] In other words, they do not consider any kind of spatial contagion among countries in the specialization process. This is quite surprising, given the strong links between countries involved in the global trade network (De Benedictis & Tajoli, 2011; Chaney, 2014) and the network structure of economic output (Hausmann & Hidalgo, 2011).

Several terms are used in the literature to describe the phenomenon of the interaction between agents (e.g., countries) being shaped by geography: spatial diffusion, spatial contagion, spatial spillover effects, and network effects. Leaving aside other disciplines (such as sociology or urban studies), the main areas of application of these concepts in economics include: economic geography and agglomeration economics (Krugman, 1991; Fujita, Krugman, & Venables, 1999; Fujita & Thisse, 2002; Duranton & Puga, 2004; Glaeser, 2008), the spatial diffusion of knowledge, technology and innovation (Comin, Dmitriev, & Rossi-Hansberg, 2012; Ertur & Koch, 2007, 2011) and mechanisms of contagion in financial markets (Allen & Gale, 2000).

What kind of channels can lead to similar patterns of export structure (in particular, the level of export diversification) among countries close to each other in geographical and/or economic terms? The first obvious channel is trade itself.[5] Whatever its driving force (differences in endowments in the Heckscher–Ohlin framework,[6] differences in productivity in the Ricardian framework, or others), international trade inevitably leads to the creation of ties among countries and to cross-country interdependence. Useful insights into possible transmission channels are also provided by endogenous growth models with international R&D spillovers, imitation of innovation, and technology diffusion (Aghion & Howitt, 1997; Howitt, 2000; Grossman & Helpman, 1991a; Coe, Helpman, & Hoffmaister, 1997) especially in a Schumpeterian multi-country setting (Ertur & Koch, 2011).

In particular, an important reference point for the study of diversification dynamics in a spatial dependence setting is still the New Trade Theory, NTT (Krugman, 1995; Neary, 2009), which explains why similar countries trade intensively, exploiting economies of scale and drawing utility gains from access to a wider variety of goods ("love of variety"). Product differentiation through "love of variety" is also a key element of New Economic Geography (NEG) models (surveyed in Fujita et al., 1999; Brakman, Garretsen, & Van Marrewijk, 2009) where the tension between agglomeration and dispersion forces determines the spatial distribution of economic activity. NEG endogenizes location in an international trade model (Brakman, Garretsen, & Van Marrewijk, 2014), so in the context of our study, one may think of the following theoretical explanation for the importance of spatial patterns and cross-country dependence in export diversification. If, in a standard two-region setting (as in Krugman, 1991), as a result of an agglomeration of forces all the production ends up in one of the regions, the degree of diversification of the remaining one goes to zero.[7] The agglomeration can also be partial, but changes in product variety offered in one unit inevitably affect the variety offered elsewhere; hence, the spatial effects cannot be ignored. The mechanism is guided by transportation costs (and, as shown by Regolo [2013], low trade costs between similar countries amplify export diversification). Whether spatial links between units (addressed in NEG framework) lead to specialization or reinforce diversification remains an important empirical question to be answered.

In this paper, we address this issue and contribute to the empirical export diversification literature by removing the assumption of spatial independence. Specifically, we study how export variety evolves as a function of economic development (GDP per capita) in the presence of spatial contagion effects. In this way, we control for the fact that a shock in the level of development of a country may affect not only the degree of specialization of this country (direct effect), but also that of all other countries with a distance decay mechanism (indirect effect). To our knowledge, this is the first paper studying the relationship between trade diversification and economic development from a spatial econometrics perspective. We employ a dynamic spatial panel data model and consider two alternative weight matrices (an inverse-distance matrix and an exponential-distance matrix).

The remainder of the paper is structured as follows. Section 2 outlines the methodology of modeling export diversification in a dynamic spatial panel setting. Section 3 discusses the properties of the data and variables. Section 4, presents and discusses the results. The final section concludes.

2 | MODELING EXPORT DIVERSIFICATION

2.1 | A dynamic spatial panel model specification

In order to take into account the highly persistent level of specialization that characterizes most of developed and developing countries, the most recent literature at the time of writing (e.g., Mau, 2016) investigates the relationship between GDP per capita and trade specialization following a dynamic approach. Here we point out that, in the presence of cross-country interdependence, standard panel estimators are likely to be biased and inconsistent (Elhorst, 2014). Thus, in order to simultaneously control for serial dependence and spatial interdependence, a dynamic spatial panel approach is needed.

The spatial econometric literature provides several alternative specifications of spatial dynamic models. A very general one includes time lags of both the dependent and independent variables, as well as contemporaneous and lagged spatial lags of both. However, as Elhorst (2014) points out, this generalized model suffers from identification problems and is not useful for empirical research. A more parsimonious model (written in vector form for a cross-section of observations at time t) can be expressed as

$$\mathbf{Y}_t = \tau \mathbf{Y}_{t-1} + \delta \mathbf{W}\mathbf{Y}_t + \eta \mathbf{W}\mathbf{Y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t \boldsymbol{\theta} + \boldsymbol{\mu} + \xi_t \boldsymbol{\iota}_N + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\mathbf{Y}_t$ denotes a $N \times 1$ column vector consisting of one observation of the dependent variable for every spatial unit ($i = 1, \ldots, N$) in the sample at time t ($t = 1, \ldots, T$), which for this study is a relative measure of export diversification. $\mathbf{X}_t$ is an $N \times K$ matrix of the explanatory variables, which here are the log of per capita GDP, the log of population, and the share of petrol-related products in overall country exports (see Section 3).

The $K \times 1$ vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ include the parameters of the explanatory variables and of their spatial lags, respectively. Coefficients τ, δ, and η are the parameters of the dependent variable lagged in time, $\mathbf{Y}_{t-1}$, in space, $\mathbf{W}\mathbf{Y}_t$, and in both space and time, $\mathbf{W}\mathbf{Y}_{t-1}$. The $N \times N$ matrix $\mathbf{W}$ is a nonnegative matrix of known constants describing the spatial arrangement of the spatial units in the sample. The specification of this matrix will be further discussed in Section 3.

The $N \times 1$ vector $\boldsymbol{\mu}$ contains spatial-specific effects μ_i, meant to control for all spatial-specific, time-invariant variables, the omission of which could bias the estimates in a typical cross-sectional study. Similarly, ξ_t denotes time-period specific effects, where $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones, controlling for all time-specific unit-invariant variables, the omission of which could also bias the estimates. These spatial and time-period specific effects are treated as fixed effects in our analysis, as it is very likely that unobserved effects are correlated with the regressor already included in the model. Finally, the elements of the disturbance term ε_t are assumed to be i.i.d. across i and t.

The parameters of model (1) are estimated using bias-corrected quasi-maximum likelihood (QML) estimators (Lee & Yu, 2010). The stationarity conditions on the spatial and temporal parameters in a dynamic spatial panel data model like (1) go beyond the standard condition $|\tau| < 1$ in serial models, and the standard condition $1/\omega_{\min} < \delta < 1/\omega_{\max}$ in spatial models (with $\omega_{\min}$ and $\omega_{\max}$ indicating the minimum and maximum eigenvalues of the $\mathbf{W}$ matrix). Indeed, to achieve stationarity in the dynamic spatial panel data model (1), the characteristic roots of the matrix $(\mathbf{I}_N - \delta\mathbf{W})^{-1}(\tau\mathbf{I}_N - \eta\mathbf{W})$ should lie within the unit circle (Elhorst, 2001; Debarsy, Ertur, & LeSage, 2012), which is the case when

$$\begin{aligned} &\tau+(\delta+\eta)\varpi_{\max}<1 \quad \textit{if} \quad \delta+\eta \geq 0\\ &\tau+(\delta+\eta)\varpi_{\min}<1 \quad \textit{if} \quad \delta+\eta<0\\ &\tau-(\delta-\eta)\varpi_{\max}>-1 \quad \textit{if} \quad \delta-\eta \geq 0\\ &\tau-(\delta-\eta)\varpi_{\min}>-1 \quad \textit{if} \quad \delta-\eta<0. \end{aligned} \tag{2}$$

2.2 | Interpretation of the model estimation

Let us now consider the interpretation of the estimation results of model (1) in terms of the impact of a variation of an independent variable on the dependent variable. As the model is estimated in implicit form, we need to rely on its reduced form to provide economic interpretations. Assuming that the matrix $(I_N - \delta\mathbf{W})^{-1}$ (known as the "global interaction multiplier") is invertible, the reduced form in (1) can be written as follows:

$$\mathbf{Y}_t=(I_N-\delta\mathbf{W})^{-1}(\tau I_N+\eta\mathbf{W})\mathbf{Y}_{t-1}+(I_N-\delta\mathbf{W})^{-1}(\mathbf{X}_t\boldsymbol{\beta}+\mathbf{W}\mathbf{X}_t\boldsymbol{\theta}+\boldsymbol{\mu}+\xi_t\boldsymbol{\iota}_N+\varepsilon_t). \tag{3}$$

Taking the partial derivatives of the expected value of $\mathbf{Y}$ with respect to each kth variable in $\mathbf{X}$ in each unit i at each time t, we then obtain the so-called impact matrices in the short run:

$$\begin{aligned} \left[\frac{\partial E(\mathbf{Y}_t)}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y}_t)}{\partial x_{Nk}}\right]_t &= \begin{pmatrix} \frac{\partial E(y_{1t})}{\partial x_{1k}} & \cdots & \frac{\partial E(y_{1t})}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_{Nt})}{\partial x_{1k}} & \cdots & \frac{\partial E(y_{Nt})}{\partial x_{Nk}} \end{pmatrix} \\ &= \left(I_N-\hat{\delta}\mathbf{W}\right)^{-1}(\hat{\beta}_k I_N+\hat{\theta}_k\mathbf{W}) \end{aligned} \tag{4}$$

and in the long run:

$$\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y})}{\partial x_{Nk}}\right]_t = \begin{pmatrix} \frac{\partial E(y_{1t})}{\partial x_{1k}} & \cdots & \frac{\partial E(y_{1t})}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_{Nt})}{\partial x_{1k}} & \cdots & \frac{\partial E(y_{Nt})}{\partial x_{Nk}} \end{pmatrix} = \left[(1-\hat{\tau})I_N - \left(\hat{\delta}+\hat{\eta}\right)\mathbf{W}\right]^{-1}\left(\hat{\beta}_k I_N + \hat{\theta}_k \mathbf{W}\right) \tag{5}$$

These matrices are generally full and not symmetric regardless of the sparsity and structure of the interaction matrix **W**. We may call the country in column j of these matrices the emitting country and the country in row i the receiving country.

For the explanatory variable x_k, the diagonal elements of the impact matrices (4) and (5) give a measure of the so-called "direct effect", that is, how much a change in the explanatory variable k for the emitting country i would affect the dependent variable for the same country i. This effect is heterogeneous across countries in the presence of spatial autocorrelation owing to higher order feedback effects. They arise as a result of impact passing through neighboring countries and back to the countries themselves. This is what Debarsy & Ertur (2010) call interactive heterogeneity, by contrast to standard individual heterogeneity in panel data models. The magnitude of these direct effects mostly depends on the value of $\hat{\beta}_k$, which is constant across the sample. Heterogeneity in the short and in the long-run direct effects thus comes from the diagonal elements of matrix $\left(I_N-\hat{\delta}\mathbf{W}\right)^{-1}$ and matrix $\left[(1-\hat{\tau})I_N-\left(\hat{\delta}+\hat{\eta}\right)\mathbf{W}\right]^{-1}$ representing the magnitude of pure feedback effects in the short and in the long run, respectively. In applied works, it is likely that the heterogeneity in the short-run direct effect is negligible compared with the value of $\hat{\beta}_k$. In the computation of the long-run direct effect, instead, the heterogeneity is amplified by the cumulative impacts of transitory shock over time.

However, the main question in this type of spatial econometric specification concerns the impact of a variation of an explanatory variable in a country i on the dependent variable in other countries of the sample. We call it the indirect or spillover effect, that is, the off-diagonal elements of the impact matrices (4) and (5). By contrast to direct effects, the main part is played here by the information content and the structure of the interaction matrix **W**, which is the main source of heterogeneity, all the parameters being constant across the whole sample. Again, in the computation of the long-run spillover effect the heterogeneity is amplified by the cumulative impact of transitory shocks over time. Not surprisingly, strongly connected countries are more influenced than less connected countries. However, spillovers diffuse to the entire sample.

The average diagonal elements of (4) and (5) can be used as a summary indicator for the short-run and the long-run direct effect (ADE), and the average row-sum of off-diagonal elements as a summary indicator of the indirect (spillover) effect (AIE). The significance levels of these short and long-run average direct and average spillover effects are bootstrapped (Elhorst, 2014). Moreover, the sum of the ith row of the impact matrices (net of the diagonal element) represents the total impact on the dependent variable in country i owing to a 1 unit change in x_k in each of the countries in the sample. The sum of the jth column of the impact matrices (net of the diagonal element) gives the total impact on the dependent variable of all countries of a 1 unit change in x_k in country j, which is of particular interest in terms of interpretation in our study.

Finally, Debarsy et al. (2012) derive the algorithms to calculate partial derivatives that can quantify the magnitude and timing of dependent variable responses in each region at various time horizons $t + T$ to changes in the explanatory variables at time t. In particular, the T-period-ahead (cumulative) impact arising from a permanent change at time t in the kth variable is:[8]

$$\frac{\partial E(\mathbf{Y}_{t+T})}{\partial x_k} = \sum_{s=0}^{T} \mathbf{D}_s [\mathbf{I}_N \beta_k + \mathbf{W}\theta_k] \tag{6}$$

where $\mathbf{D}_s = (-1)^s \left(\mathbf{B}^{-1} + \mathbf{C}\right)^s \mathbf{B}^{-1}$, $s=0, \ldots, T–1$, $\mathbf{B} = (\mathbf{I}_N - \rho\mathbf{W})$, and $\mathbf{C} = -(\tau\mathbf{I}_N + \eta\mathbf{W})$.

The main diagonal elements of the $N \times N$ matrix sums in (6) for time horizon T represent (cumulative) own-region impacts that arise from both time and spatial dependence. The sum of off-diagonal elements of this matrix reflects both spillovers measuring contemporaneous cross-partial derivatives, and diffusion measuring cross-partial derivatives that involve different time periods.[9]

3 | DATA AND VARIABLES

To estimate model (1), we use a balanced panel dataset of 114 (both developed and developing) reporter countries[10] and 2,394 observations over the years 1992 to 2012, covering the overwhelming proportion of world trade.[11] Export data are drawn from the United Nations Commodity Trade Statistics Database (UN Comtrade database, retrieved through the WITS database) at the highest level of disaggregation available for international comparisons (5,016 product lines) in the Harmonized System of goods classification.[12] In line with Cadot et al. (2011) and Parteka and Tamberi (2013a), we use mirrored exports.

Trade data are used to compute measures of export diversification for each country and time period. Given that we are interested in the links between countries and dependence between their trade structures, we choose to assess each country's export composition with respect to the overall trend (referring each country's degree of export diversity to other countries). Hence, following the empirical literature on the topic (De Benedictis et al., 2008, 2009; Parteka & Tamberi, 2013a; Mau, 2016), we employ relative measures of diversification. Specifically, the Relative Theil entropy index (*RelTheil*) is our preferred measure and is computed for each time period as:

$$RelTheil_i = \sum\nolimits_{j=1}^{m} \left(s_{ij} \cdot \ln \frac{s_{ij}}{w_j} \right), \quad RelTheil_i \in \langle 0, \ln(m) \rangle, \tag{7}$$

where $s_{ij} = \frac{x_{ij}}{\sum_j x_{ij}}$ are the shares of the exports (x) of product j ($j = 1,2,\ldots, m$) in the total exports of country i ($i = 1,2,\ldots, n$) and $w_j = \frac{\sum_i x_{ij}}{\sum_i \sum_j x_{ij}}$ is the average share of product j in total world exports.[13]

The explanatory variables included in model (1) are the logarithm of GDP per capita (ln*GDPpc*) at *PPP* constant 2005 international dollars, and the logarithm of population (ln*POP*), both obtained from the World Bank's World Development Indicators Database. ln*GDPpc* is used as a measure of economic development level, whereas ln*POP* is a proxy for country size (Mau, 2016).[14] Additionally, in order to account for the degree of dependence on petrol, using UN Comtrade data we compute the share of petrol-related products in overall country exports (*Oil*).[15]

Table 1 shows summary statistics for the aforementioned variables, before applying the logarithms. We observe a high variability (in terms of min/max differences) in the values of the export diversification index, indicating that countries with a very highly specialized export structure coexist in our panel

TABLE 1 Description of variables and summary statistics

Variable	Description	Obs.	Mean	*SD*	Min	Max
RelTheil	Relative Theil index	2,394	2.8409	1.4986	0.3739	8.0463
GDPpc	GDP per capita, PPP const. 2005 U.S.$	2,394	10,125	11,330	420	53,878
POP	Population (millions)	2,394	49.6	158	0.980	1,350
Oil	Share of petrol in total exports	2,394	0.13	0.24	0	0.98

with ones with a very diversified structure. Similarly, the per capita income of the countries ranges from only US$420 to US$53,578, with a mean of US$10,125, suggesting great heterogeneity in the level of development among countries. In our sample there are also countries with a considerable share of petrol in their total exports (the maximum of the *Oil* variable equals 0.98); they are likely to have a different export structure to all the other countries so this variable is usually taken into account in panel data studies on export diversification as an additional covariate (Cadot et al., 2011; Parteka & Tamberi, 2013a; Mau, 2016).

We further explore the characteristics of the data, assessing the presence of cross-sectional dependence and unit root in the four variables described above. We first test for cross-sectional correlation using Pesaran's (2004) CD test. The CD statistics computed for the entropy measure (*RelTheil*) is very high (98.8) and significant, confirming the existence of cross-sectional dependence (Table 2). Applying the same test on the residuals of an AR(2) model (to accommodate for serial correlation), we obtain a lower CD value (7.3) still highly significant. Similar comments hold for the three explanatory variables (ln*GDPpc*, ln*POP*, and *Oil*), except for the lack of evidence of residual cross-sectional dependence in the AR(2) model for ln*POP*. To assess the stationarity of the raw data, we use the panel unit root test proposed by Pesaran (2007), which is robust against cross-sectional dependence. Even controlling for a deterministic trend, the t values of the test suggest that the null hypothesis of a unit root cannot be rejected in the case of *RelTheil*, ln*POP*, and *Oil*. These results give a strong indication regarding the stationarity of the raw data and their cross-sectional dependence, and suggest to apply the two tests (CD test and panel unit root test) also to the residuals of the spatial dynamic model (1) to see whether the expected (conditional) diversification patterns over space and time are stationary.

Finally, spatial lags of the variables are computed using two alternative spatial weights matrices. The first one (**W**1) is an inverse-distance matrix, whose general term is defined as:

TABLE 2 Pesaran (2004) test for cross-sectional dependence in panels (CD test) and Pesaran (2007) panel unit root test robust against cross-sectional dependence

	CD test without control for serial correlation	CD test with control for serial correlation	Panel unit root test robust against CD (t values)
RelTheil	98.78***	7.26***	−1.847
ln*GDPpc*	251.46***	65.57***	−2.611**
ln*POP*	211.12***	−0.23	−1.528
Oil	119.21***	73.62***	−1.572

Note. *,**,*** Denote significance at the 1%, 5%, 10% levels, respectively. Deterministic component included in the panel root test: trend; number of lags included: 4.

$$w1_{ij}=\begin{cases} 0 & \text{if } i=j \text{ and if } d_{ij}>\overline{d} \\ d_{ij}^{-1}/\sum_{j\neq i} d_{ij}^{-1} & \text{otherwise} \end{cases}, \tag{8}$$

where d_{ij} is the great-circle distance between the centroids of the countries and $\overline{d}$ is a cut-off value equal to 3,843 km, which corresponds to the minimum distance that allows all countries to have at least one neighbor. The second matrix (**W**2) is an exponential-distance matrix, whose general term is defined as:

$$w2_{ij}=\begin{cases} 0 & \text{if } i=j \text{ and if } d_{ij}>\overline{d} \\ e^{-d_{ij}}\Big/\sum_{j\neq i} e^{-d_{ij}} & \text{otherwise.} \end{cases} \tag{9}$$

Both matrices are row-standardized.

4 | ESTIMATION RESULTS

4.1 | Estimated average direct and indirect (spillover) effects

Table 3 reports the bias-corrected QML estimation results of the spatial dynamics Equation (1) obtained using the balanced panel dataset and the two alternative weighting matrices **W** described in

TABLE 3 Dynamic spatial model—QML estimates

	Dep. Variable: *RelTheil*	
	W1	**W2**
$\mathbf{Y}_{t-1}$	0.575*** (37.756)	0.577*** (37.956)
$\mathbf{WY}_{t}$	0.228*** (4.850)	0.255*** (6.061)
$\mathbf{WY}_{t-1}$	–0.064 (–1.119)	–0.125** (–2.356)
$\mathbf{lnGDPpc}_{t}$	–0.185*** (–3.612)	–0.185*** (–3.636)
$\mathbf{lnPop}_{t}$	–0.407*** (–2.908)	–0.354** (–2.491)
$\mathbf{WlnGDPpc}_{t}$	–0.135 (–1.088)	–0.158 (–1.363)
$\mathbf{WlnPop}_{t}$	0.152 (0.720)	0.061 (0.303)
$corr^2$	0.571	0.571
Log-lik.	−114.43	−111.13
Spatial effects	YES	YES
Time effects	YES	YES
$\hat{\tau}+\hat{\delta}+\hat{\eta}-1$	−0.261	−0.293
CD test on the residuals	1.121	1.468
Unit root-test on the residuals (*t* value)	−2.698***	−2.750***

Note. Sample: all countries (114). Period: 1992–2012. **W1** is an inverse distance matrix; **W2** is an exponential distance matrix; *t* statistics in parentheses. *,**,***Denote significance at the 1%, 5%, 10% levels respectively.

Section 3. The dependent variable ($\mathbf{Y}_t$) is *RelTheil*, which captures the role of the extensive margin of diversification and reveals the best distributional properties for disaggregated export data while its qualitative interpretation is equal to the alternative measures (Mau, 2016).[16]

The two main explanatory variables included in the $\mathbf{X}_t$ matrix of model (1) are: (i) the log of GDP per capita ($\mathbf{lnGDPpc}_t$), approximating the level of technological development of the country; and (ii) the log of the population size ($\mathbf{lnPop}_t$), capturing the effect of exporter sizes, and thus to proxy for factor costs (assumed to be lower in large countries owing to internal factor competition). As mentioned in the introduction, some authors found a hump-shaped relation between export diversification and growth, suggesting to include polynomial expansion terms of per capita income in the model. However, some preliminary checks support the argument of Mau (2016) that the nonmonotonic pattern is mainly because of an omitted log-transformation of the income variable. Thus, in our model specification we do not include a quadratic term for $\mathbf{lnGDPpc}_t$. We additionally control for the heterogeneity in the patterns of trade diversification between oil exporters and other countries by including the share of petrol-related products in overall country exports (*Oil*). Finally, the model includes country (μ), as well as time-specific effects (ξ_t) to control for time-invariant unobserved heterogeneity and time-common effects.

As $\mathbf{RelTheil}_t$ decreases with diversification and increases with specialization, we expect a negative impact of $\mathbf{lnGDPpc}_t$ and $\mathbf{lnPop}_t$. While the explanatory variables are in log values, the dependent variable is not logged because its distribution is not as extreme as GDP per capita. Thus, the marginal effects must be interpreted as semi-elasticities. The right-hand side of the model also includes time and spatial lags of the dependent variable, that is, $\mathbf{Y}_{t-1}$, $\mathbf{WY}_t$, and $\mathbf{WY}_{t-1}$, as well as spatial lags of the explanatory variables, $\mathbf{WX}_t$. Separate columns of Table 3 refer to the results obtained with the two different weights matrices (**W1** and **W2**) used for the estimation.

The stationarity conditions are always satisfied. First, the sum of the serial, spatial, and spatio-temporal autoregressive coefficients, $\tau + \delta + \eta$, of the variables $\mathbf{Y}_{t-1}$, $\mathbf{WY}_t$ and $\mathbf{WY}_{t-1}$, turns out to be 0.739 in the case of **W1**, and 0.707 in the of **W2**. Consequently, $\tau + \delta + \eta - 1$ (reported in Table 3) is lower than zero, suggesting that controlling for spatio-temporal persistence is sufficient to satisfy the stationarity condition (2). The CD test applied to the residuals of the models are 0.121, using the **W1** matrix, and 0.468 using the **W2** matrix. These values are not statistically different from zero, indicating that all the cross-sectional dependence revealed in the raw data has been accounted for using the spatial Durbin dynamic specification (1). Finally, the *t* values of the panel unit root test on the residuals are -2.698, using the **W1** matrix, and -2.750 using the **W2** matrix. Both of them are statistically significant, indicating that the null hypothesis of unit root can be rejected.

Table 3 shows that the two explanatory variables, $\mathbf{lnGDPpc}_t$ and $\mathbf{lnPop}_t$ are always statistically significant and the coefficients associated with these variables have the expected negative sign. In contrast, the corresponding spatial lags, $\mathbf{WlnGDPpc}_t$ and $\mathbf{WlnPop}_t$, do not enter the model significantly. Moreover, the results obtained with the alternative **W** matrices are very similar, confirming the robustness of the choice of spatial weights. However, as widely discussed in Subsection 2.2, the estimated coefficients cannot be interpreted as marginal effects, as they do not take into account spillover and feedback effects.

The novelty of our study in the context of export diversification literature lies in assessing direct and indirect (spillover) effects. On the basis of the econometric results reported in Table 3, we have computed the average direct and indirect marginal effects of the two main explanatory variables ($\mathbf{lnGDPpc}_t$ and $\mathbf{lnPop}_t$) on the entropy measure $\mathbf{RelTheil}_t$, using Equations (4) and (5). The results are reported in Table 4. Inference on these impacts is based on simulating 1,000 values of these impacts. Using both spatial weights matrix **W1** and **W2**, the short- and long-run direct effects are all significant and have the expected negative sign. These findings suggest that, in line with the predictions of

TABLE 4 Marginal effects and bootstrapped *t* values

	Dep. Variable: *RelTheil*	
	W1	**W2**
	Short-run effects	
ADE—**lnGDPpc**$_t$	–0.188*** (–3.799)	–0.191*** (–3.898)
AIE—**lnGDPpc**$_t$	–0.225 (–1.462)	–0.271** (–1.949)
ATE—**lnGDPpc**$_t$	–0.413*** (–2.783)	–0.462*** (–3.279)
ADE—**lnPop**$_t$	–0.406*** (–3.037)	–0.358*** (–2.681)
AIE—**lnPop**$_t$	–0.119*** (–2.423)	–0.122*** (–2.345)
ATE—**lnPop**$_t$	–0.526*** (–3.007)	–0.481*** (–2.668)
	Long-run effects	
ADE—**lnGDPpc**$_t$	–0.455*** (–3.986)	–0.455*** (–3.988)
AIE—**lnGDPpc**$_t$	–0.694* (–1.682)	–0.637** (–1.912)
ATE—**lnGDPpc**$_t$	–1.149*** (–2.663)	–1.092*** (–3.032)
ADE—**lnPop**$_t$	–0.972*** (–3.047)	–0.852*** (–2.696)
AIE—**lnPop**$_t$	–0.652 (–1.488)	–0.399 (–1.457)
ATE—**lnPop**$_t$	–1.624*** (–2.453)	–1.252*** (–2.465)

Note. Sample: all countries (114). Period: 1992–2012. **W1** is an inverse distance matrix; **W2** is an exponential distance matrix; *t* statistics in parentheses; *,**,***Denote significance at the 1%, 5%, 10% levels respectively. ADE, direct marginal effect; AIE, indirect marginal effect; ATE, average total effect (ADE + AIE).

endogenous growth models (Grossman & Helpman, 1991a,b; Acemoglu & Zilibotti, 1997), the Ricardian-based Eaton and Kortum model (Mau, 2016) and the related empirical literature on the determinants of export diversification (Parteka & Tamberi, 2013b), a higher level of development and a bigger country size stimulate diversification.

How to interpret it? Making investments in new fields of activities are associated with uncertainty about future outcomes, and potentially also with sunk costs that cannot be recovered in the case of failure. Capital indivisibilities require a minimum stock of capital in order to make such investments possible. Consequently, richer (in terms of per capita income) and larger countries have more possibilities of starting risky projects. In other words, richer countries export more goods because their superior production technology endows them with an absolute advantage in global markets. Moreover, large countries can compensate for lower fundamental productivity with lower factor costs.

As shown in Table 4, the short-run direct semi-elasticities are slightly higher than the estimated parameter, because of higher order feedback effects in the expression (4). In particular, the short-run semi-elasticity of a change in per capita GDP is −0.191 (using **W2**). Moreover, consistently with our expectations, the long-run direct effects are much stronger than the short-run direct effects. In particular, the long-run semi-elasticity of a change in per capita GDP is −0.455 using **W2**. This is because it takes time before trade diversification levels change.

The average indirect effects have the same sign as the direct effect. Using the **W2** matrix, both short-run and long-run spatial spillover effects of GDP per capita are indeed negative and significant.

Increases in GDP per capita of a country have a positive impact not only on its own trade diversification, but also on the diversification of other countries, with a distance decay effect. In particular, the average long-run spillover effect (AIE) of a change in per capita GDP is -0.637 using **W2**. Thus, knowledge spillovers reinforce the absolute technological advantage of countries and allow them to export more goods. The average indirect effect of population is also statistically significant and negative in the short run, and not statistically significant (at least at 10 percent) in the long run. Thus, spatial proximity to large countries accelerates the diversification process at least in the short run, since the lower factor costs of the neighbors (which compensate for lower fundamental productivity) can easily be imported. In line with our expectations again, the long-run indirect effects are much stronger than the short-run indirect effects. Using the **W1** matrix, spatial spillover effects of GDP per capita are still negative, but only weakly significant. Thus, we may conclude that the matrix **W2** is more adequate to capture the existence of spatial spillover effects.

How long does it take to reach the long-run equilibrium? To answer this question, using the algorithm (6) presented in Section 2 and the exponential spatial weights matrix **W2**, we calculate the T-period-ahead (cumulative) average direct (ADE) and indirect (AIE) impact arising from a permanent change at time t in per capita GDP. In the case of ADE, the value at time zero corresponds to the pure average feedback effect, while subsequent values capture the impact arising from time dependence of country i on changes in its own explanatory variables plus some of the feedback loop effects, which will be fed forward in time. In the case of AIE, the initial value gives the average magnitude of the contemporaneous spillover effect, while subsequent values represent space–time diffusion effects. Considering a very long time horizon (30 years), the results of our computation (not reported but available upon request) suggest that in about 10 years the whole space–time diffusion of this shock is widely completed.

4.2 | Spatial diffusion of diversification shocks—cross-country heterogeneity results

Up to now, we have discussed the average direct and spillover effects and we have given an economic interpretation of these results. However, the interactive heterogeneity characterizing the marginal effects in spatial econometric models (see Subsection 2.2) merits a deeper discussion of the spatial diffusion of shocks in the observed terms of the model.

Thus, using matrix **W2**, we provide evidence of this heterogeneity focusing on the long-run impacts of a change of per capita GDP (the main variable of interest) in a selected group of countries on their own export diversification (direct impacts), and on the degree of export diversification of all other countries (indirect impacts). The selected countries are the United States, Japan, four European countries (Germany, France, Italy, and Poland), and the so-called BRICS (Brazil, Russia, India, China, and South Africa). In order to simplify the interpretation of the results, the marginal effects of per capita GDP on the entropy (*RelTheil*) for each country i are taken with the opposite sign. Consequently, we can assess a marginal effect on the level of export diversification, rather than on the entropy.

Figure 1(a) presents the long-run direct marginal impact, that is, the effect of a change in GDP per capita for the emitting country i on the degree of export diversification for the same country i. As discussed in Subsection 2.2, this marginal impact, computed using the diagonal element of the impact matrix (5), in the presence of spatial autocorrelation is heterogeneous across countries owing to higher order feedback effects that arise as a result of impacts passing through neighboring countries and back to the countries themselves. However, as expected, we do not observe much difference between countries, because of the fact that feedback effects are of small scale compared with the estimated value of the parameter associated to $\mathbf{lnGDPpc}_t$. The direct impacts are indeed slightly higher in Japan and in

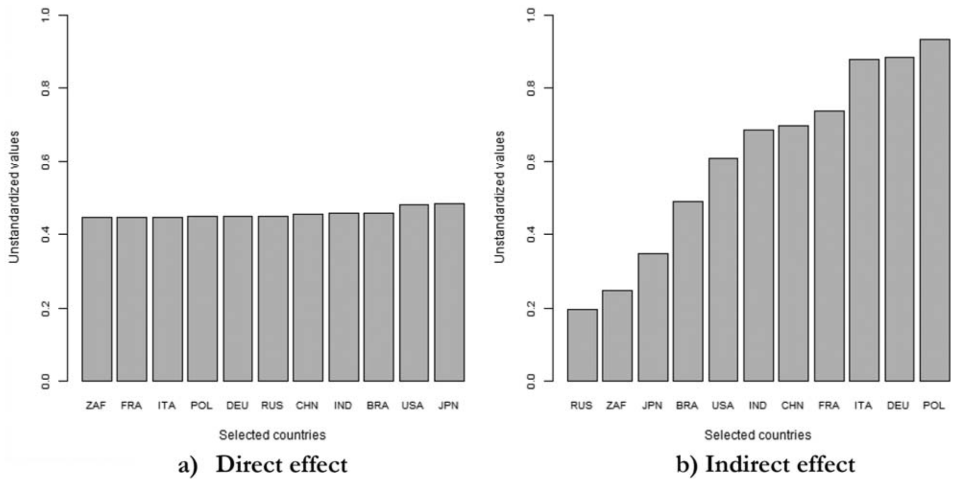

FIGURE 1 Long-run direct and indirect (spillover) effects of a change in per capita GDP on export diversification (selected countries). (a) Direct effect; (b) Indirect effect

Note. Marginal effects of per capita GDP on the entropy (*RelTheil*) for each country i are taken with the opposite sign. Selected countries: United States (USA), Japan (JPN), Germany (DEU), France (FRA), Italy (ITA), Poland (POL), Brazil (BRA), Russia (RUS), India (IND), China (CHN), and South Africa (ZAF). Computations are based on the use of the exponential distance matrix (**W2**)

the United States (with a semi-elasticity of 0.48) than in the European countries and in the BRICS (with a semi-elasticity of 0.45).

Figure 1(b) reports the long-run spillover effects of per capita GDP for the selected group of countries, that is, the total impact of a 1 percent change in the per capita GDP in country j on the degree of export diversification of all countries. They are computed using the sum of the jth column of the impact matrix (5) (net of the diagonal element). The picture emerging from Figure 1(b) is very different from the one in Figure 1(a). Indirect impacts are indeed strongly heterogeneous across countries. In particular, spatial spillovers from European countries (especially from Poland, Germany, and Italy) are much higher than those from the other countries. This result is not surprising given that European countries are more densely connected in space than the other selected countries. Specifically, we note that Poland is the country (within the selected group) that diffuses the most of its development to other countries, with a semi-elasticity of 0.93, followed by Germany and Italy. Thus, a 1 percent increase in per capita GDP in Poland generates a 0.93 increase in the degree of export diversification of all other countries, an impact that is much higher than that reported for highly developed and industrialized countries such as the United States (0.61), and Japan (0.35). In contrast, Russia and South Africa are the countries that diffuse the least. Of course, spillovers from European (emitting) countries diffuse to the entire sample, but they will be more strongly received within Europe.

As a final remark, it is important to observe that QML estimators for dynamic spatial panel models (as used so far) are based on the assumption that there are only exogenous covariates except for the time and spatial lag terms. In order to check for the robustness of the results to endogeneity biases (as a result of, for example, simultaneity),[17] we have also used the System-GMM (Generalized Method of Moments) estimator (Blundell & Bond, 1998) in place of QML to estimate model (1), as suggested by Kukenova and Monteiro (2008). The results from two-step System-GMM robust estimations with Windmeijer's (2005) finite-sample correction,[18] strongly confirm the main conclusions obtained using the QML estimator: a higher level of development and larger country size exert a positive effect on the export diversification of countries (bearing in mind that *RelTheil* is an inverse measure of export diversity), with indirect effects reinforcing the direct impact.

5 | CONCLUSIONS

In this paper we have proposed an extension to the existing literature on the export diversification–development relationship. In particular, we have relaxed the implicit assumption of cross-country independence that has characterized all previous empirical works in this field. Our argument is that international trade in goods and cross-border mobility of factors of production make countries strongly interdependent. Consequently, a shock in the characteristics of one country (e.g., with respect to its income) is likely to have an impact not only on its own performance but also on the performance of all other countries, with a distance decay effect. Given the relationship between export diversity and GDP per capita, the transmission of shocks results in spatial dependence in terms of diversification too.

We have employed a spatial dynamics panel data specification, which has allowed us to capture short- and long-run, direct and indirect (spatial spillover) effects. The sample of countries analyzed is very broad (114 economies at all stages of development, observed between 1992 and 2012, covering more than 90 percent of all trade exports) and we base our results on product level export data.

We have found that spatial network effects are indeed very important in determining the impact of GDP per capita and country size on the degree of export diversification. On the one hand, our results confirm the predictions of endogenous growth models: richer countries export more goods because their superior production technology endows them with an absolute advantage in global markets, while large countries exploit economies of scale and can compensate for lower fundamental productivity with lower factor costs. These are known as direct effects.

On the other hand, our findings reveal that indirect effects strongly reinforce direct effects: spatial spillovers strengthen the absolute technological advantage of countries and allow them to export a greater variety of goods. Moreover, spatial proximity to large countries accelerates the diversification process, since lower factor costs of neighbors (that compensate for lower fundamental productivity) can easily be imported.

We find that in about 10 years the whole space–time diffusion of the diversification shock is widely completed. Additionally, we examined cross-country heterogeneity in the spatial diffusion of diversification shocks. We reveal that indirect impacts are indeed strongly heterogeneous across countries. In particular, spatial spillovers from European countries (especially from Poland, Germany and Italy) are much higher than those from the other countries, such as the United States, Japan, or the BRICS.

To the best of our knowledge, there is no theoretical contribution that directly explains export diversity in a spatial dependence framework. However, we strongly believe that by studying, for the first time, the relationship between trade diversification and economic development from a spatial econometrics perspective we do provide a noticeable empirical insight into a fuller understanding of export diversification mechanism.

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NOTES

[1] In general, the theoretical motivation for the study of export diversification patterns is rather weak. The exception is a contribution by Mau (2016) who provides a relevant theoretical illustration of the link between diversification and economic growth based on Ricardian framework (Eaton & Kortum, 2002): richer countries are likely to export more goods

because their superior production techniques endow them with an absolute advantage in global markets, and there is no re-specialization. Regolo (2013) develops an extension of the Romalis (2004) framework and models how a country's export diversification varies across destination markets (export diversification is greater if the trade partner has similar endowments).

[2] Theoretically, such a situation can take place when countries are "travelling across multiple cones of diversification" (Deardorff, 2000; Schott, 2003; Cadot et al., 2011). Countries initially diversify at the extensive margin, but when a high level of development is reached it is more profitable to abandon the production of labor-intensive goods and, thus, re-specialize.

[3] Absolute measures (such as the Herfindahl index or the Theil index), based on indices of concentration or inequality, were used by Imbs and Wacziarg (2003), Koren and Tenreyro (2007), Cadot et al. (2011), Agosin, Alvarez, and Bravo-Ortega (2012), and Klinger and Lederman (2006). Relative measures were employed by De Benedictis et al. (2008, 2009), Parteka & Tamberi (2013a,b) and Mau (2016).

[4] Some authors only take into account the role played by distance between trade partners. For instance, Agosin et al. (2012) consider the GDP-weighted average distance of each country from its trading partners, whereas Dennis and Shepherd (2011) take into account the distance between the exporting country and Germany. These measures proxy for transportation costs. Theoretical framework by Regolo (2013) shows that trade costs matter for diversification.

[5] Some diversification studies only address this issue indirectly by including in the set of additional explanatory variables the participation in common regional trade agreements (Parteka & Tamberi, 2013b).

[6] Along these lines, the model by Regolo (2013) predicts that exports between similarly endowed countries ("South–South" and "North–North") are more diversified than exports between differently endowed countries ("South–North" and "North–South").

[7] Similar reasoning can be made in a multiregional NEG setting. See a thorough review of the state of the art in geographical economics and spatial economic analysis, including multiregional framework, in Commendatore, Kubin, and Kayam (2015).

[8] By a permanent change of x_k at time t they mean: $x_{kt}+\Delta, x_{k,t+1}+\Delta, \ldots, x_{k,T}+\Delta$, so the values increase to a new level and remain there in future time periods.

[9] The term spillover is referred to contemporaneous cross-partial derivatives, those that involve the same time period. Cross-partial derivatives involving different time periods are referred to as diffusion effects, since diffusion takes time.

[10] The countries are: Albania; Algeria; Angola; Armenia; Australia; Austria; Azerbaijan; Bangladesh; Belarus; Benin; Bolivia; Brazil; Bulgaria; Burkina Faso; Burundi; Cameroon; Canada; Central African Republic; Chad; Chile; China; Colombia; Congo, Rep.; Costa Rica; Cote d'Ivoire; Denmark; Dominican Republic; Ecuador; Egypt, Arab Rep.; El Salvador; Finland; France; Gabon; Gambia, The; Georgia; Germany; Ghana; Greece; Guatemala; Guinea; Guinea-Bissau; Honduras; Hong Kong SAR, China; Hungary; India; Indonesia; Israel; Italy; Japan; Jordan; Kazakhstan; Kenya; Korea, Rep.; Kyrgyz Republic; Lao PDR; Latvia; Lebanon; Lithuania; Madagascar; Malawi; Malaysia; Mali; Mauritania; Mauritius; Mexico; Moldova; Mongolia; Morocco; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; Norway; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Romania; Russian Federation; Rwanda; Saudi Arabia; Senegal; Sierra Leone; Singapore; Slovenia; South Africa; Spain; Sri Lanka; Sweden; Switzerland; Tajikistan; Tanzania; Thailand; Togo; Trinidad and Tobago; Tunisia; Turkey; Turkmenistan; Uganda; Ukraine; United Kingdom; United States; Uruguay; Uzbekistan; Venezuela, RB; Vietnam; Yemen, Rep.; Zambia.

[11] The estimation of dynamic spatial panel data models requires balanced data. The countries considered correspond to 90.7 percent of world trade (own calculations based on export data, 2012, from UN Comtrade). Microstates (defined as countries with a population below 1 million) are excluded from the analysis.

[12] A similar level of detail is adopted by Klinger and Lederman (2006), Cadot et al. (2011), Parteka and Tamberi (2013a), and Mau (2016).

[13] We have also considered relative Gini index (*RelGini*) and the dissimilarity index (*DI*) as additional measures (see Parteka [2010] for exact formulas). The higher the values of the indices, the less diversified (the more specialized) is the export structure of the country under investigation. However, the results obtained with these alternative measures of export diversification are qualitatively similar to those obtained with the relative entropy index. Thus, we do not report them in the paper.

[14] Given the high correlation (0.69) between the logs of our crucial dependent variable (per capita income) and GDP, in order to avoid multicollinearity issues we decide to use data on population instead (the correlation coefficient between the logs of *POP* and *GDPpc* is equal to only 0.05). In our sample, the correlation between the logs of *GDP* and *POP* is equal to 0.75, while that between the logs of land area and *POP* is equal 0.62, so population can be considered a good proxy of country size.

[15] Specifically, this variable is obtained with the use of product-level export statistics (HS 6-digit level) as a share of product lines 270900, 271000, 271011, 271119, 271129, 271210, 271311, 271312, 271320, and 271390 in overall country exports.

[16] We have checked the correlation between the *RelTheil* index and other measures of diversification used in the related literature: the Gini index and the conventional Theil entropy measure (both in absolute terms, as in (Cadot et al., 2011). The correlation between them and our index—*RelTheil*—is very high (0.71 for the Gini index and 0.74 for the absolute Theil index).

[17] Arguments that trade diversification generates economic growth are present in papers by Al-Marhubi (2000), Feenstra and Kee (2008), Herzer and Nowak-Lehnmann (2006), and Hesse (2008). Using System-GMM to estimate a nonspatial dynamic model and testing for reverse causality and potential feedback effects, Mau (2016) shows that GPD per capita is weakly exogenous and that diversification also has an impact on GDP per capita.

[18] The results are presented in the full working paper version of the paper.

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