Human capital spillovers and regional development*

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Abstract

This paper introduces technological interdependence into the theoretical framework of Gennaioli et al. (2013). This extension leads to an expression for regional development with spatial effects that motivates the incorporation of the geographical dimension into their newly constructed database and empirical analysis. Our estimation results corroborate both the necessity of accounting for the presence of spatial dependence to study the determinants of regional income per capita and the importance of educational attainment in explaining regional development differences. Furthermore, we provide evidence that human capital generates positive spatial spillovers.

JEL classification: C12, C21, O47, R11.

Keywords: Regional development, technological interdependence, human capital, spatial Durbin model, spillover effects.

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1 Introduction

Gennaioli et al. (2013, GLLS hereafter) develop a 'Lucas-Lucas' model that considers both talent allocation between entrepreneurship and work and *within-region* human capital externalities in a standard migration framework. The main aim of this theoretical framework is to study the determinants of regional development, emphasizing the channels through which human capital affects total factor productivity (TFP). Nevertheless, the possible influence of neighboring regions is not taken into account and, as a consequence, the spatial dimension of the data is neglected. Given that it is widely acknowledged that outcomes in a given region are related to the outcomes and characteristics of its neighbors, we extend the model developed by GLLS by introducing technological interdependence between regions *à la* Ertur and Koch (2007).

2 A 'Lucas-Lucas' model with technological interdependence

GLLS considers a country with productive (P) and unproductive (U) regions, populated by uniformly distributed agents whose utility depends on consumption (c) and housing (a): $u(c, a) = c^{1-\phi}a^{\phi}$. Half of these agents are 'rentiers' and the rest are 'laborers'. The latter are endowed with h units of human capital and can become either workers or entrepreneurs. While workers in region i earn a wage ϖ_i, entrepreneurs obtain a profit from the production of the consumption good according to

$$y_{i,h} = A_i h^{1-\varphi-\tau-\kappa} H_{i,h}^{\varphi} K_{i,h}^{\kappa} T_{i,h}^{\tau}, \quad \varphi + \tau + \kappa < 1 \tag{1}$$

where A_i denotes regional TFP, $H_{i,h}$ is workers' human capital, $K_{i,h}$ is physical capital and $T_{i,h}$ is land.

Following Ertur and Koch (2007), we consider that TFP in a given region depends not only on its amount of labor L_i, average level of human capital $E_i(h)$ and idiosyncratic factors $\tilde{A}_i$, but also on technological spillovers from other regions:

$$A_i = \tilde{A}_i [E_i(h)^{\psi} L_i]^{\zeta} \prod_{j \neq i} A_j^{\rho w_{ij}} \tag{2}$$

where $\psi \geqslant 1$ reflects the relative importance of human capital quality with respect to quantity and $\zeta > 0$ captures the scope of *within-region* human capital externalities.

The specification for TFP in (2) takes into account the influence of productivity levels in neighboring regions through the term $\prod_{j \neq i} A_j^{\rho w_{ij}}$. The degree of technological interdependence is captured by $0 \leqslant \rho < 1$. Although this parameter is the same for all regions, the net effect of these spatial externalities depends on the relative connectivity between a region and its neighbors, determined by the exogenous, non-stochastic and finite friction terms $0 \leqslant w_{ij} \leqslant 1$, if $j \neq i$; $w_{ij} = 0$, otherwise. For the sake of clarity, it will be assumed in what follows that, for region i, $\sum_{i \neq j} w_{ij} = 1$.

In a first period, laborers choose both the location and occupation that maximize their income and housing markets clear according to each region's total amount of labor. Given that regional productivity is considered as given in this first period, the introduction of technological interdependence does not alter regional labor allocation with respect to that in the original model. In a second period, entrepreneurs hire land and human and physical capital, production is carried out and consumption takes place.

This theoretical framework is operative when the ratio of wages between productive and unproductive regions is greater than one: $\frac{\varpi_P}{\varpi_U} = \left(\frac{\tilde{A}_P \Pi_P}{\tilde{A}_U \Pi_U}\right)^{\frac{1}{1-\kappa}} \left(\frac{E_P(h)^{\psi} L_P}{E_U(h)^{\psi} L_U}\right)^{\frac{\zeta}{1-\kappa}} \left(\frac{H_U}{H_P}\right)^{\frac{\tau}{1-\kappa}} > 1$, where $\Pi_P = \prod_{P,j \neq P,i} A_{P,j}^{\rho w_{ij}}$ and $\Pi_U = \prod_{U,j \neq U,i} A_{U,j}^{\rho w_{ij}}$. This ratio increases with the relative importance of human capital quality with respect to quantity. Given that $\tilde{A}_P > \tilde{A}_U$, this effect is magnified in the presence of technological interdependence. As pointed out by Dettori et al. (2012), TFP tends to be geographically concentrated and, hence, it can be expected that $\Pi_P > \Pi_U$. If $(\tau - \psi\zeta)(1-\phi) + \phi(1-\kappa) > 0$, there is a stable equilibrium allocation characterized by a threshold for the human capital endowment h_m above which laborers migrate such that $h_m \left[1 - \left(\frac{\tilde{A}_U \Pi_U}{\tilde{A}_P \Pi_P}\right)^{\frac{1-\phi}{1-\kappa}} \left(\frac{L_P}{L_U}\right)^{\frac{\zeta(\zeta-1)(1-\phi)}{1-\kappa}} \left(\frac{H_P}{H_U}\right)^{\frac{(1-\phi)(\tau-\zeta\psi)+(1-\kappa)\phi}{1-\kappa}}\right] = \chi$. This cut-off value increases with mobility costs (χ) and decreases with the influence of technology in neighboring regions.

Aggregating individual production functions in (1), and imposing some equilibrium conditions, it is obtained that regional output is given by

$$Y_i = C A_i^{\frac{1}{1-\kappa}} H_i^{\frac{1-\tau-\kappa}{1-\kappa}}, \quad C > 0 \tag{3}$$

where $C > 0$ is a constant determined by the model parameters.

Taking natural logarithms in expressions (2) and (3), and rewriting them in matrix form for N regions, we get

$$
\begin{aligned}
A &= \tilde{A} + \zeta L + \zeta\psi E(h) + \rho W A \qquad (4)\\
Y &= C + \frac{1}{1-\kappa}A + \frac{1-\kappa-\tau}{1-\kappa}H \qquad (5)
\end{aligned}
$$

If $\rho \neq 0$ and $\frac{1}{\rho}$ is not an eigenvalue of W, we can solve for A in (4) and substitute it into (5), obtaining

$$
Y = C + \frac{1}{1-\kappa}(I_N - \rho W)^{-1}\tilde{A} + \frac{\zeta}{1-\kappa}(I_N - \rho W)^{-1}[L + \psi E(h)] + \frac{1-\kappa-\tau}{1-\kappa}H \qquad (6)
$$

The Mincerian approach permits the derivation of empirical predictions from the formulation of the average level of human capital in region i as a first-order expansion around the average levels of the Mincerian return ($\bar{\mu}_i$) and years of schooling ($\bar{S}_i$): $E(h) = \bar{\mu}\bar{S}$, in matrix notation. Bearing in mind that $H = E(h) + L$, denoting $y = Y - L$, and after some algebraical manipulations, it is found that

$$
y = \left(\frac{1}{1-\kappa}\right)\tilde{A} + \left(1 + \frac{\zeta\psi-\tau}{1-\kappa}\right)\bar{\mu}\bar{S} + \left(\frac{\zeta-\tau}{1-\kappa}\right)L - \rho\left(\frac{1-\kappa-\tau}{1-\kappa}\right)W\bar{\mu}\bar{S} + \rho\left(\frac{\tau}{1-\kappa}\right)WL + \rho W y \quad (7)
$$

By rewriting equation (7) for region i, we obtain an expression for regional development with spatial effects similar to equation (16) in GLLS in the absence of technological interdependence ($\rho = 0$):

$$
\begin{aligned}
\ln\left(\frac{Y_i}{L_i}\right) &= \left(\frac{1}{1-\kappa}\right)\ln\tilde{A}_i + \left(1 + \frac{\zeta\psi-\tau}{1-\kappa}\right)\bar{\mu}_i\bar{S}_i + \left(\frac{\zeta-\tau}{1-\kappa}\right)\ln L_i - \qquad (8)\\
&\quad -\rho\left(\frac{1-\kappa-\tau}{1-\kappa}\right)\sum_{j\neq i}^{N} w_{ij}\bar{\mu}_j\bar{S}_j + \left(\frac{\rho\tau}{1-\kappa}\right)\sum_{j\neq i}^{N} w_{ij}\ln L_j + \rho\sum_{j\neq i}^{N} w_{ij}\left(\frac{Y_j}{L_j}\right)
\end{aligned}
$$

This theoretical result allows us to conclude that output per capita in a region depends not only on its own factors but also on the level of development as well as on some of its determinants in neighboring regions. As a consequence, it can be stated that the effects of human capital may not be confined to a particular territory in the present framework.

3 Empirical analysis

Following expression (8), we incorporate the spatial dimension into the data set constructed by GLLS with a shapefile containing regional boundaries. The main source[1] from which this geospatial information has been extracted is the GADM database (version 2.0). Unfortunately, its administrative division for regions does not coincide with that considered by GLLS. In order to match the two data sets, lower-level administrative divisions in the GADM database were merged for some countries[2]. It was also necessary to remove regions for which no data were available and to reshape some spatial units.

3.1 Narrow replication and spatial dependence assessment

GLLS examine the determinants of regional development by regressing (log) income per capita on geography and education while controlling for population, institutions, culture and country fixed-effects. A narrow replication of the results obtained by these authors can be found in Table 1. Our extension of their theoretical framework suggests that, in the presence of technological interdependence, regional development should not be analyzed as if spatial dependence was a secondary aspect. In order to confirm this impression, we have studied the existence of spatial autocorrelation in the residuals of the OLS regressions by calculating the global Moran's I test statistic of spatial randomness. The presence of significant spatial autocorrelation in the residuals implies that they are not independent, clustering together in space, and may be an indication of some type of model misspecification.

Knowledge spillovers and their productivity effects are geographically concentrated (Fischer et al., 2009). For this reason, we consider that, in the present context, the strength of spatial relationships is determined by geographical proximity. The dependence structure among regions has been established using four specifications of the spatial weights matrix based on proximity and constructed from the geographical coordinates. The presence of a non-trivial number of islands in GLLS data prevents us from using a binary matrix based on geographical contiguity. Nevertheless, we have applied an alternative contiguity

[1] A shapefile for Latvian 'rajoni' was kindly provided by Maris Nartiss. NUTS-2 divisions for Denmark, Ireland, Portugal and Romania were obtained from Eurostat.

[2] Azerbaijan, Belgium, Burkina Faso, Bulgaria, Czech Republic, Dominican Republic, Egypt, Gabon, United Kingdom, Guatemala, Hungary, Ireland, Kazakhstan, Cambodia, South Korea, Sri Lanka, Moldova, Malawi, Nigeria, Philippines, Romania, Serbia, Sweden, Thailand, Turkey, Uganda, and Uzbekistan.

criterion that, using Delaunay triangulation, connects all regions without an intervening neighbor, ensuring that all of them have, at least, one neighbor. This 'Gabriel' weights matrix, largely used in computer science and ecology, considers two regions to be neighbors if no other region falls between the circles of radius equal to their respective shortest distances. The other three specifications for the spatial weights matrix correspond to another binary type that establishes a specific number of n-nearest neighbors ($n = 3, 5, 7$).

The values obtained for global Moran's I test statistic (z-scores) are reported in the lower panel of Table 1. Regardless of the weights matrix used, OLS residuals present positive spatial autocorrelation in all the specifications used by GLLS to analyze the determinants of regional development. This result suggests the use of spatial econometric techniques to study the factors that explain regional differences in income per capita worldwide.

3.2 Wide replication and spatial spillover effects

Expression (8) includes both endogenous interaction effects among the dependent variable and exogenous interaction effects among the explanatory variables. Therefore, its empirical counterpart is the spatial Durbin model (SDM):

$$y = \alpha\iota_N + X\beta + WX\theta + \rho Wy + \varepsilon \tag{9}$$

where y is a (Nx1) vector of the logarithms of income per capita, α is the intercept and ι_N is a (Nx1) vector of ones. X is a (Nxk) matrix of k exogenous variables and β is its associated (kx1) parameter vector. W is a (NxN) row-standardized[3] spatial weights matrix and WX is a (Nxk) matrix of the spatial lags of the exogenous variables. θ is its corresponding (kx1) parameter vector. Wy is the (Nx1) vector with the spatial lag of the endogenous variable and ρ is the spatial autocorrelation parameter. ε is a (Nx1) vector of error terms.

The spatial lag Wy is endogenous due to simultaneous spatial interactions and, hence, it is correlated with the error term. For this reason, the estimation of (9) has been performed

[3] Although not required, row-standardization is desirable in contiguity schemes so that each neighbor of a region is given equal weight. This enhances the understanding of spatial autocorrelation measures and coefficients because spatial lags correspond to the weighted average of neighboring observations, allowing us to obtain comparable spatial parameters across different samples with different connectivity structures.

using maximum likelihood (ML). The results are displayed[4] in Table 2 for the spatial weights matrix that, for each specification, achieves the highest value of the log-likelihood function. The main conclusions drawn from Table 1 are maintained, i.e., that regions nearer to the coast and with better resource endowments tend to have higher income per capita. It can also be observed that the introduction of spatial effects does not affect the robustness of human capital as a determinant of regional development.

In contrast to the results obtained by GLLS, we find that population – one of the main variables in expression (8) – is now statistically significant. Furthermore, the estimation of the spatial model leads to a positive and statistically significant relationship between the index of institutional quality and regional income per capita. More importantly, and corroborating our theoretical extension, the spatial lag of the dependent variable and the spatial interaction effects of population and educational attainment are statistically significant in all the specifications. These results are reinforced by the inability of global Moran's I test statistic to reject the null hypothesis of no spatial autocorrelation in the estimation residuals at conventional significance levels (one-tailed test). It can also be observed that likelihood ratio (LR) tests prefer the SDM to alternatives that include a single type of spatial interactions.

The interpretation of parameter estimates in spatial regression models is more complicated than in standard OLS regressions due to the dependence relationships in the spatial lag terms that generate feedback effects. A change in an explanatory variable in a given region will not only have a direct effect on its dependent variable, but also an indirect effect on that of its neighbors. Nevertheless, this is a valuable feature of spatial models that permits the quantification of spillover effects. Table 3 shows the marginal effects of regional income per capita determinants obtained from the SDM estimation, calculated using the method proposed by LeSage and Pace (2009). The sign of the average direct effects displayed in its upper panel tends to coincide with that of the estimated parameters for regional development determinants. The differences between parameter estimates and direct impact estimates represent the feedback effects passing through neighboring regions and back to the origin itself. The figures reported in the lower panel suggest that the

[4] We do not report the results for the specification that includes the educational attainment of older people, considered by GLLS to assess the possible presence of simultaneity bias problems.

indirect effects generated by distance to the coast are positive. On the contrary, those generated by oil production are negative. It can also be observed that the spatial spillovers related to population, social capital and ethnic diversity are not statistically significant.

Last, but not least, we focus on indirect effects generated by human capital. These spatial spillovers can be interpreted as the effects from a change in the educational level of all regions by a constant on the level of income per capita of a typical region. The average indirect effect of educational attainment is positive and statistically significant in specifications with a wider coverage. Although their magnitude is small compared to the average direct effects (around 30%), this finding provides evidence of the presence of positive human capital externalities *between regions*. In line with our theoretical extension, this implies that a higher stock of human capital in a region entails not only a higher technological level for that economy, but also additional technological flows into its neighbors.

Our estimation results also provide evidence of a negative indirect effect of educational attainment in specifications that refer to a smaller number of regions, where less developed countries are mainly represented. This may be reflecting that the adverse effects of the regional competition for the educated population are higher than the benefits from the exchange of knowledge and experience between neighboring regions. Nonetheless, we find that institutional quality exerts positive spatial spillover effects in these specifications.

References

Dettori B, Marrocu E, Paci R. 2012. Total factor productivity, intangible assets and spatial dependence in the European regions. *Regional Studies* **46**: 1401–1416.

Ertur C, Koch W. 2007. Growth, technological interdependence and spatial externalities: Theory and evidence. *Journal of Applied Econometrics* **22**: 1033–1062.

Fischer MM, Bartkowska M, Riedl A, Sardadvar S, Kunnert A. 2009. The impact of human capital on regional labor productivity in Europe. *Letters in Spatial and Resource Sciences* **2**: 97–108.

Gennaioli N, La Porta R, Lopez-de Silanes F, Shleifer A. 2013. Human capital and regional development. *Quarterly Journal of Economics* **128**: 105–164.

LeSage J, Pace RK. 2009. *Introduction to spatial econometrics*. Boca Raton: Chapman & Hall/CRC.

Table 1: Regional income per capita, geography, institutions, culture, and education. OLS estimation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature	−0.016*	−0.013	−0.007	0.000	−0.014	0.002	−0.009*
	(0.008)	(0.008)	(0.005)	(0.006)	(0.009)	(0.008)	(0.005)
Inverse distance to coast	1.028***	0.524***	0.507	0.581**	0.457***	0.571*	0.884***
	(0.208)	(0.138)	(0.326)	(0.238)	(0.129)	(0.340)	(0.255)
Oil production per capita	0.165***	0.185***	0.160	0.146**	0.198***	0.104	0.140**
	(0.048)	(0.047)	(0.097)	(0.059)	(0.049)	(0.201)	(0.064)
Years of education		0.276***	0.348***	0.303***	0.265***	0.368***	
		(0.017)	(0.021)	(0.028)	(0.018)	(0.044)	
Population		0.012	0.001	0.009	0.017	0.005	−0.026
		(0.016)	(0.021)	(0.018)	(0.017)	(0.039)	(0.018)
Institutional quality			0.367			0.467	
			(0.230)			(0.285)	
Trust in others				−0.041		0.044	
				(0.088)		(0.163)	
Ethnic groups					−0.050**	0.001	
					(0.024)	(0.049)	
Years of education 65+							0.252***
							(0.028)
Constant	9.583***	6.616***	5.724***	6.186***	6.779***	5.354***	8.253***
	(0.227)	(0.244)	(0.467)	(0.315)	(0.217)	(0.776)	(0.311)
Observations	1,536	1,499	483	728	1,498	281	608
Number of countries	107	105	78	66	105	45	39
Within Adjusted R^2	8%	42%	62%	48%	42%	62%	39%
excluding institutions and culture	8%	42%	61%	48%	42%	62%	39%
excluding education	8%	10%	6%	12%	15%	16%	9%
Between Adjusted R^2	49%	64%	60%	53%	64%	58%	63%
excluding institutions and culture	49%	64%	58%	53%	64%	55%	63%
excluding education	49%	39%	39%	38%	43%	49%	36%
Moran's I							
Gabriel	11.372***	11.305***	2.727***	5.127***	11.205***	4.895***	5.673***
n=3 nearest neighbors	11.856***	11.541***	3.149***	5.185***	11.397***	4.827***	7.122***
n=5 nearest neighbors	13.641***	13.352***	3.349***	7.293***	13.126***	4.413***	7.685***
n=7 nearest neighbors	14.421***	15.222***	4.000***	8.873***	14.881***	5.697***	8.794***

Note: The endogenous variable is (log) income per capita. Regressions include country fixed-effects. Robust standard errors reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Moran's I test statistics (z-score) refer to estimation residuals and have been calculated using four binary spatial weights matrices, all based on geographical proximity and row-standardized.

Table 2: Regional income per capita, geography, institutions, culture, and education. SDM estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.009	0.003	−0.004	0.000	0.007	−0.001
	(0.006)	(0.005)	(0.008)	(0.001)	(0.006)	(0.010)
Inverse distance to coast	1.496***	1.193	0.883**	0.358	1.035***	0.831**
	(0.320)	(0.273)	(0.380)	(0.321)	(0.314)	(0.390)
Oil production per capita	0.155***	0.155***	0.208**	0.124**	0.229***	0.282
	(0.038)	(0.031)	(0.091)	(0.062)	(0.034)	(0.229)
Years of education		0.219***	0.227***	0.215***	0.219***	0.212***
		(0.010)	(0.014)	(0.015)	(0.011)	(0.019)
Population		0.037***	0.060***	0.056***	0.036***	0.086***
		(0.010)	(0.019)	(0.015)	(0.011)	(0.025)
Institutional quality			0.579**			0.697***
			(0.187)			(0.002)
Trust in others				−0.006		0.039
				(0.121)		(0.210)
Ethnic groups					−0.076***	−0.033
					(0.024)	(0.039)
W * Income per capita	0.861***	0.793***	0.713***	0.872***	0.835***	0.725***
	(0.011)	(0.013)	(0.027)	(0.014)	(0.014)	(0.032)
W * Temperature	−0.023***	−0.005	−0.003	−0.000	−0.010	−0.008
	(0.006)	(0.005)	(0.009)	(0.001)	(0.006)	(0.011)
W * Inverse distance to coast	−1.012***	−0.881***	−0.383	−0.147	−0.663*	−0.388
	(0.345)	(0.291)	(0.426)	(0.362)	(0.345)	(0.452)
W * Oil production per capita	−0.057	−0.027	−0.013	−0.035	−0.113**	0.122
	(0.062)	(0.045)	(0.137)	(0.096)	(0.049)	(0.327)
W * Years of education		−0.159***	−0.168***	−0.181***	−0.170***	−0.180***
		(0.011)	(0.018)	(0.016)	(0.013)	(0.022)
W * Population		−0.035***	−0.059***	−0.049***	−0.022*	−0.073***
		(0.012)	(0.022)	(0.017)	(0.014)	(0.029)
W * Institutional quality			0.004			−0.293
			(0.252)			(0.289)
W * Trust in others				0.050		−0.217
				(0.152)		(0.265)
W * Ethnic groups					0.083**	−0.022
					(0.033)	(0.054)
Constant	1.019***	1.125***	1.755***	0.604***	0.621***	1.820***
	(0.110)	(0.146)	(0.323)	(0.218)	(0.163)	(0.427)
Weights matrix	knn5	knn3	knn3	knn5	gab	knn3
Observations	1,536	1,499	483	728	1,498	281
Number of countries	107	105	78	66	105	45
Log-likelihood	−1163.711	−899.923	−279.919	−408.122	−1000.61	−117.648
Moran's I	0.799	−1.017	0.328	1.063	−4.241	0.236
LR tests						
SAR vs. SDM	27.332***	223.831***	91.336***	16.139***	202.423***	71.363***
SEM vs. SDM	56.690***	27.330***	12.394*	5.536	26.518***	13.386*

Note: The endogenous variable is (log) income per capita. Standard errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Moran's I test statistics (z-score) refer to estimation residuals.

Table 3: Marginal effects of regional income per capita determinants. SDM estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Direct effects						
Temperature	0.003	0.001	−0.006	0.000	0.005	−0.011
	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)	(0.010)
Inverse distance to coast	1.611***	1.221***	0.968***	0.438	1.130***	1.093***
	(0.299)	(0.248)	(0.341)	(.303)	(0.285)	(0.331)
Oil production per capita	0.187***	0.195***	0.255***	0.159***	0.266***	0.680
	(0.041)	(0.033)	(0.097)	(0.061)	(0.037)	(0.588)
Years of education		0.225***	0.224***	0.218***	0.225***	0.179***
		(0.009)	(0.014)	(0.014)	(0.100)	(0.021)
Population		0.035***	0.054***	0.056***	0.040***	0.073**
		(0.010)	(0.018)	(0.015)	(0.011)	(0.033)
Institutional quality			0.723***			0.957***
			(0.203)			(0.357)
Trust in others				0.015		−0.191
				(0.082)		(0.302)
Ethnic groups					−0.067***	−0.090
					(0.025)	(0.068)
Indirect effects						
Temperature	−0.100***	−0.011	−0.018	−0.007	−0.024*	−0.020
	(0.012)	(0.010)	(0.014)	(0.027)	(0.014)	(0.015)
Inverse distance to coast	1.834***	0.289	0.773	1.191	1.123*	0.519
	(0.693)	(0.459)	(0.605)	(1.046)	(0.663)	(0.550)
Oil production per capita	0.508	0.421**	0.425	0.524	0.438**	0.790
	(0.338)	(0.164)	(0.370)	(0.489)	(0.219)	(0.741)
Years of education		0.063***	−0.021	0.047	0.068*	−0.065**
		(0.023)	(0.037)	(0.060)	(0.036)	(0.031)
Population		−0.023	−0.053	0.001	0.043	−0.025
		(0.032)	(0.045)	(0.200)	(0.053)	(0.048)
Institutional quality			1.308*			0.514
			(0.694)			(0.572)
Trust in others				0.321		−0.457
				(0.701)		(0.482)
Ethnic groups					0.110	−0.112
					(0.132)	(0.106)

Note: Standard errors reported in parentheses. The empirical distribution of these marginal effects have been obtained by simulating the SDM parameters using the maximum likelihood multivariate normal distribution (10,000 draws). *** p<0.01, ** p<0.05, * p<0.10.