Knowledge Spillovers: The Impact of Genetic Distance and Data Revisions

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Abstract

This paper investigates the role of genetic distance and data revisions for knowledge spillovers. The basic framework is a model developed by Ertur and Koch (2007), which accounts for technological interdependence among countries through spatial externalities and models interdependence via an interaction matrix based on geographic distance. In contrast, in this paper, data on genetic distance from Spolaore and Wacziarg (2009) is used for the interaction matrix. It is found that, whereas in the original model spatial knowledge spillovers from capital investment were insignificant, with genetic distance, these indirect impact estimates now have a significant effect on steady-state income per worker. However, the estimation results imply an implausibly large capital share of income. Finally, the original version relies on data from PWT 6.1. This data has been extensively revised in more recent versions of the PWT (Johnson et al., 2013). It is shown that results for both distance measures are not robust across different versions of the PWT.

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1 Introduction

Countries do not develop in isolation from each other, but are connected and interact in many different ways. A key aspect of this interdependence concerns technology, in particular technological knowledge spillovers. Accounting for this technological interdependence both on an empirical and theoretical level requires a notion on how to model the interaction between countries. Empirical evidence suggests that knowledge spillovers decline with the geographic distance between countries (Keller, 2002, 136). This insight has, for instance, been picked up by Ertur and Koch (2007), who develop a theoretical model of economic growth that incorporates technological knowledge spillovers between countries. In the empirical part of their paper, they employ a specification which qualitatively replicates the effect identified by Keller (2002). However, geographic distance is only one possible measure to model interaction between countries. The concept is more general and encompasses "any kind of network structure" (Ertur and Koch, 2011, 236). For example, data on genetic distance, which is defined as the time, since two populations have shared a common ancestor (Spolaore and Wacziarg, 2009, 470), can be used to build this structure. Ertur and Koch (2007) acknowledge this possibility.

This paper contributes to the cross-country growth literature by using the data set on genetic distance from Spolaore and Wacziarg (2009) to assess the robustness of the empirical results in Ertur and Koch (2007). Spolaore and Wacziarg (2009) demonstrate that genetic distance has an effect on cross-country income differences. They propose the following mechanism and also provide empirical evidence consistent with it: Within populations, characteristics (e.g. habits, implicit beliefs or conventions) are transmitted across generations biologically and culturally, and genetic distance can be viewed as a summary statistic that measures a divergence across populations in characteristics that are slowly changing over time. In the next step, they assume that these differences in characteristics between populations hinder the diffusion of technology.

Apart from the general feasibility of utilizing genetic distance to assess robustness of the results in Ertur and Koch (2007), a second motivation for employing data on genetic distance is that via this approach interactions between economies might be captured that geographic distance is missing. For instance, Lindner and Strulik (2014, 18) note (without any reference to genetic distance) that it might be the case that knowledge exchange between the United States and Great Britain is higher than between the United States and Guatemala even though geographic distance would suggest otherwise. By modeling interaction through genetic distance instead of geographic distance however, stronger knowledge spillovers between the United States and Great Britain compared to between the United States and Guatemala would be in line with the data on genetic distance, as the United States and Great Britain populations are genetically closer to each other than the ones in the United States and Guatemala. Geographic distance would imply the strength of the knowledge spillovers to be reversed.

A second contribution of this paper is the assessment of the robustness of the results in Ertur and Koch (2007) to data revisions. In their econometric analysis, they rely on data from Penn World Table (PWT) Version 6.1 (Heston et al., 2002). Since the publication of their article, newer versions of the PWT have become available, and in each update the data has been revised. Ideally, empirical results should be robust to different versions of the PWT. However, this is not a foregone conclusion, and Ponomareva and Katayama (2010) find that conclusions from cross-country growth studies might change, even for the same period and units of observation, depending on the version of the PWT. More recently, Johnson et al. (2013) have also investigated this issue. They find that some data revisions have been relatively minor. For instance, the average growth rate of GDP over the period 1975-1999 for Morocco was 1.6% when calculating it using PWT 6.1 and 1.7% when basing the calculations on PWT 6.2 (Johnson et al., 2013, Table 1). Other revisions were drastic, showing high variability in the estimates, as exemplified by the case of Equatorial Guinea. Taking the data from PWT 6.1, its average GDP growth rate in the period 1975-1999 was -2.7%, making it the worst performing of 40 African countries that are covered in both PWT 6.1 and 6.2. On the other hand, for the data from PWT

6.2, its average GDP growth rate over the same period was 4%, thereby becoming the second-best performer in the list of 40 African countries after Botswana (Johnson et al., 2013, 255-256). Hence, the fact that robustness to different versions is an issue for some studies is not too surprising. However, they also argue, based on the results of a series of replication exercises for prominent articles investigating economic growth that results from cross-sectional estimations tend to be robust to changing the version of the PWT. This paper investigates whether this is also the case for the results in Ertur and Koch (2007) by estimating the model for the same set of countries and the same time period (1960-1995), but with data also taken from PWT Versions 6.2 and 7.1. The importance of checking the robustness of a study's results to data revisions has been highlighted, for example, in the debate on the relationship between public debt levels and economic growth (see Reinhart and Rogoff (2010) and Herndon et al. (2014)).

The third contribution of this paper lies in the quantification of the strength of the indirect (spillover) effects from e.g. physical capital investment on steady-state per worker income in the model by Ertur and Koch (2007) through the method suggested by LeSage and Pace (2009). In the original study, only the magnitude of the direct effects is presented.

The paper is organized as follows: Section 2 introduces the concept of genetic distance, and Section 3 presents the main building blocks of the model by Ertur and Koch (2007). In Section 4, the empirical specification and estimation strategy are derived and Section 5 presents and discusses the estimation results. Section 6 concludes.

2 Genetic Distance

Genetic data is increasingly used in economic studies.[1] Nonetheless, a brief summary of relevant concepts might be helpful in order to better understand what genetic distance actually measures. A gene, i.e. a string of DNA encoding a protein, can exist in numer-

[1] See, for instance, Spolaore and Wacziarg (2009), Giuliano et al. (2014), Desmet et al. (2011) or Ashraf and Galor (2013).

ous forms, and a particular form of this gene is called an allele (Giuliano et al., 2014, 182). Individuals with different alleles may have different observable (phenotypic) traits, for instance, eye color; although different alleles between individuals need not result in different observable characteristics (ibid.). It is important to note that the frequency of alleles is not constant across populations, as this is the information used to calculate measures of genetic distance between populations (Spolaore and Wacziarg, 2009, 480). In principle, on which particular genes' allelic frequency[2] this computation is based would not matter. In practice, however, it is based on neutral genes. These are genes that do not endow an individual with a selective advantage (Giuliano et al., 2014, 182). This implies that the measure of genetic distance provides no information about specific genes that have a direct impact on fitness and survival or income and productivity (Spolaore and Wacziarg, 2009, 470).

The particular index of genetic distance mainly considered in this paper, F_{ST} distance, measures the probability that the alleles for a gene, selected at random from two populations, will be different (Spolaore and Wacziarg, 2009, 481).[3] For identical allele distributions, this index equals zero, and it increases with differences in the distributions.[4] As Spolaore and Wacziarg (2009) argue, these allele differences increase due to the presence of random (or genetic) drift. When populations become separated, and for constant drift rates, genetic distance can be used to measure the time that has passed, since populations have become separated (or in other words their degree of genealogical relatedness). It is in this sense that genetic distance can be understood as the time that has elapsed, since populations have shared a common ancestor. Spolaore and Wacziarg (2009, 470-471) furthermore hypothesize that genetically more distant populations, have diverged more strongly in characteristics that are variably transmitted across generations, like habits or implicit beliefs, and that this divergence hinders, for instance, communication and under-

[2] A database on allele frequencies is available under: `http://alfred.med.yale.edu`.

[3] Data from Spolaore and Wacziarg (2009) on an index with different theoretical properties (Nei's distance), which is highly correlated with F_{ST} distance, will serve to assess robustness.

[4] This index from Cavalli-Sforza et al. (1994) uses the frequency of 128 alleles related to 45 genes, fulfilling the conditions that they are selectively neutral and easy to collect (Giuliano et al., 2014, 183).

standing and thereby creates barriers to the diffusion of development or technology. They illustrate this with the example that one learns easier from siblings than from cousins, but in turn also easier from cousins than from strangers. Applying this line of thought to the example mentioned in the introduction: The United States are genetically closer to Great Britain than to Guatemala (the respective pairwise genetic distances are 0.033 and 0.091, respectively) so that with regard to this concept fewer barriers to knowledge diffusion should exist between the United States and Great Britain than between the United States and Guatemala.[5] Note that the stated genetic distances in this example are weighted F_{ST} genetic distances, taking into account that some countries (e.g. the US), consist of genetically distant subpopulations (see Spolaore and Wacziarg, 2009, 484-485).

3 Model Setup

The aggregate production for each country $i = 1, \ldots, N$ at time t in the model developed by Ertur and Koch (2007) is described by the Cobb-Douglas production

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \qquad \text{with} \qquad 0 < \alpha < 1 \tag{3.1}$$

where output, Y_{it}, is produced with the three input factors labor, L_{it}, physical capital, K_{it}, and technology, A_{it}. This function is linearly homogenous in capital and labor. The aggregate level of technology in region i at time t is described by

$$A_{it} = \Omega_t k_{it}^{\phi} \prod_{j \neq i}^{N} A_{jt}^{\gamma w_{ij}}. \tag{3.2}$$

[5] Considering the geographic distances between the country capitals would suggest otherwise, as Washington, D.C. is closer to Guatemala City (distance: 3,007km) than to London (distance: 5,909km). The distances are calculated with the spherical law of cosines and $R_{\oplus} = 6378.1$km as the earth's equatorial radius

$$d_{ij} = R_{\oplus} \times \arccos[\cos lat_i \cos lat_j \cos(long_i - long_j) + \sin lat_i \sin lat_j].$$

Basically, overall technological progress is assumed to be due to three different factors in equation (3.2) which are (imperfect) substitutes. The first factor, Ω_t, reflects exogenous (neutral) technological progress as modeled in the original contribution by Solow (1956, 85). In formal terms, this is captured by $\Omega_t = \Omega_0 e^{\mu t}$, with μ the constant rate of technological progress and Ω_0 the initial level.

The second term models the influence of physical capital per worker, $k_{it} = \frac{K_{it}}{L_{it}}$, on aggregate technology in country i. The level of technology increases with the level of capital per worker k_{it}, modeling the assumption that physical capital externalities exist. Their strength is governed by the parameter ϕ for which $0 \leq \phi < 1$ holds so that perfect knowledge spillovers from capital investment in a given firm in country i to the remaining firms in this country are ruled out, as some knowledge is "lost in transmission". Modeling the assumption that all firms in a region gain a higher level of technology, if one firm increases its physical capital per worker is due to Arrow (1962) and Romer (1986). The assumption that these knowledge spillovers should be constrained within a single country is however tenuous. Why should knowledge diffuse only within a country, but not across countries? The strength of the spillovers might be dampened (see e.g. Keller (2002) for empirical evidence), but they should be present nonetheless.

The third factor in equation (3.2) picks this up. From a formal perspective, this factor is a weighted geometric mean of the level of technology in all countries $j = 1, \ldots, N$ connected to country i. The strength of these cross-border spillovers or spatial externalities is governed by two factors. The parameter γ, for which $0 \leq \gamma < 1$ holds, gauges which fraction of knowledge generated in, for example, country j' spills over into country i. This value is the same for all units of observation. The second factor concerns the weights w_{ij}. In general, these are allowed to differ across countries, and they specify the way in which countries are connected to each other. It is important to note that how strong country i benefits from knowledge spillovers depends on the way it is connected to all other countries under consideration. This implies that the net effect on a country's level of technology due to spatial spillovers will differ across countries. For a given degree of spillovers, relatively isolated countries will benefit less than more integrated countries. With respect to the spatial weights, it is assumed that these are non-negative, reflecting that countries might not be connected to each other so that spatial exteranalities are absent, non-stochastic, implying that the weights are fixed over time, and finite. In addition, the weights w_{ij} lie in the interval $[0,1]$ and for $i = j$, $w_{ij} = 0$ holds, excluding the case of self-influence. Finally, the weights sum to one.[6] In sum, the spatial weight matrix or, more generally, interaction matrix, $\mathbf{W}$, is thus row-stochastic (LeSage and Pace, 2009, 9-10).

Taking logs of (3.2) leads to

$$\ln A_{it} = \ln \Omega_t + \phi \ln k_{it} + \gamma \sum_{j \neq i}^{N} w_{ij} \ln A_{jt}$$

or written in matrix form for all countries (at time t)

$$\boldsymbol{A} = \boldsymbol{\Omega} + \phi \boldsymbol{k} + \gamma \boldsymbol{W} \boldsymbol{A} \iff \boldsymbol{A} = (\boldsymbol{I} - \gamma \boldsymbol{W})^{-1} \boldsymbol{\Omega} + \phi (\boldsymbol{I} - \gamma \boldsymbol{W})^{-1} \boldsymbol{k}. \tag{3.3}$$

The equivalence follows, given that spatial dependence is positive $\gamma \neq 0$ and that the inverse $(\boldsymbol{I} - \gamma \boldsymbol{W})^{-1}$ exists.[7] Using the result $(\boldsymbol{I} - \gamma \boldsymbol{W})^{-1} = \sum_{r=0}^{\infty} \gamma^r \boldsymbol{W}^r$, the level of technology for a given country i can be written as

$$A_{it} = \Omega_t^{\frac{1}{1-\gamma}} k_{it}^{\phi} \prod_{j=1}^{N} k_{jt}^{\phi \sum_{r=1}^{\infty} \gamma^r (\boldsymbol{W}^r)_{ij}} \tag{3.4}$$

where $(\boldsymbol{W}^r)_{ij}$ are the individual entries in row i and column j of the matrix $\boldsymbol{W}$, taken to the power of r. The production function can be written in per-capita terms as $y_{it} = A_{it} k_{it}^{\alpha}$, where $y_{it} = \frac{Y_{it}}{L_{it}}$. Inserting the level of technology in (3.4) into this equation leads to

$$y_{it} = \Omega_t^{\frac{1}{1-\gamma}} \cdot k_{it}^{u_{ii}} \cdot \prod_{j \neq i}^{N} k_{jt}^{u_{ij}}, \tag{3.5}$$

[6] On these assumptions, see Ertur and Koch (2007, 1036) or Fischer and Wang (2011, 20).

[7] This inverse exists, if $\frac{1}{\gamma}$ is not an eigenvalue of the spatial weight matrix. An application of Gerschgorin's Circle Theorem demonstrates this (Gerschgorin, 1931).

where $u_{ii} \equiv \alpha + \phi \left(1 + \sum_{r=1}^{\infty} \gamma^r (\boldsymbol{W}^r)_{ii}\right)$ and $u_{ij} \equiv \phi \sum_{r=1}^{\infty} \gamma^r (\boldsymbol{W}^r)_{ij}$.

From equation 3.5 it can be seen that in contrast to the standard Solow model, the model presented here implies heterogeneity in the social elasticities of income per worker with respect to capital per worker. If, for instance, region i increases its own stock of physical capital per worker, the social return (elasticity) is

$$\frac{\partial y_{it}}{\partial k_{it}} \frac{k_{it}}{y_{it}} = u_{ii}.$$

If, however, all regions $i = 1, \ldots, N$ jointly increase their stocks of physical capital per worker, then the elasticity is

$$\frac{\partial y_{it}}{\partial k_{it}} \frac{k_{it}}{y_{it}} + \sum_{j \neq i}^{N} \frac{\partial y_{it}}{\partial k_{jt}} \frac{k_{jt}}{y_{it}} = u_{ii} + \sum_{j \neq i}^{N} u_{ij} = \alpha + \frac{\phi}{1 - \gamma} < 1. \tag{3.6}$$

The inequality is assumed by Ertur and Koch (2007, 1037) to avoid endogenous growth.

Capital accumulates according to $\dot{k}_{it} = s_i y_{it} - (n_i + \delta) k_{it}$, where $\dot{k}_{it} = dk_{it}/dt$ denotes a time derivative, s_i is the country specific constant saving rate (the fraction of output invested in physical capital), n_i is the constant growth rate of labor for country i, and δ is the depreciation rate, which is identical for all countries.

Due to the decreasing returns to capital per worker, k_{it} converges monotonically to its steady-state value or value on the balanced growth path, k^*_{it}. When this value is reached, capital (and by implication output) per worker grow at the balanced growth rate g.[8]

Calculating the steady-state value for y^*_{it}, using the expression for the the capital-output ratio on the balanced growth path and taking logs, leads to the result

$$\begin{aligned} \ln y^*_{it} = & \frac{1}{1-\alpha-\phi} \ln \Omega_t + \frac{\alpha+\phi}{1-\alpha-\phi} \ln s_i - \frac{\alpha+\phi}{1-\alpha-\phi} \ln(n_i + g + \delta) \\ & - \frac{\alpha\gamma}{1-\alpha-\phi} \sum_{j \neq i}^{N} w_{ij} \ln s_j + \frac{\alpha\gamma}{1-\alpha-\phi} \sum_{j \neq i}^{N} w_{ij} \ln(n_j + g + \delta) + \frac{\gamma(1-\alpha)}{1-\alpha-\phi} \sum_{j \neq i}^{N} w_{ij} \ln y^*_{jt}. \end{aligned}$$

[8] The balanced growth rate is given by $g = \mu \left[(1-\alpha)(1-\gamma) - \phi\right]^{-1}$.

4 Empirical Specification, Estimation Strategy, and Model Interpretation

4.1 Econometric Specification of the Model

The last equation in the previous section has the empirical counterpart at $t = 0$

$$
\begin{aligned}
\ln y_i^* = &\beta_0 + \beta_1 \ln s_i + \beta_2 \ln(n_i + g + \delta) + \theta_1 \sum_{j \neq i}^{N} w_{ij} \ln s_j \\
&+ \theta_2 \sum_{j \neq i}^{N} w_{ij} \ln(n_j + g + \delta) + \rho \sum_{j \neq i}^{N} w_{ij} \ln y_j^* + \varepsilon_i
\end{aligned}
\tag{4.1}
$$

where $\frac{1}{1-\alpha-\phi} \ln \Omega(0) = \beta_0 + \varepsilon_i$ for $i = 1, \ldots, N$, β_0 is a constant and ε_i is a country-specific shock. The empirical specification above implies the following theoretic constraints on the coefficients: $\beta_1 + \beta_2 = 0$ and $\theta_1 + \theta_2 = 0$. In matrix form, (4.1) is equivalent to[9]

$$
\boldsymbol{y} = \boldsymbol{\iota_N} \beta_0 + \boldsymbol{X\beta} + \boldsymbol{WX\theta} + \rho \boldsymbol{Wy} + \boldsymbol{\varepsilon}. \tag{4.2}
$$

Here $\boldsymbol{y}$ is an $N \times 1$ vector of real income per worker in logarithms, $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones, and β_0 is a scalar. $\boldsymbol{X}$ is an $N \times 2$ matrix of the explanatory variables (investment rate and population growth rate) in logarithms, $\boldsymbol{\beta}$ is a 2×1 vector $[\boldsymbol{\beta} = (\beta_1, \beta_2)']$ of the regression parameters for the investment rate and population growth rate, $\boldsymbol{W}$ is the $N \times N$ interaction matrix in row-standardized form, $\boldsymbol{WX}$ is the $N \times 2$ matrix of the spatial lag of $\boldsymbol{X}$. $\boldsymbol{\theta}$ is a 2×1 vector $[\boldsymbol{\theta} = (\theta_1, \theta_2)']$ of the regression parameters for the spatially lagged explanatory variables, ρ is the spatial autoregressive coefficient, $\rho = \frac{\gamma(1-\alpha)}{1-\alpha-\phi}$, and, finally, $\boldsymbol{\varepsilon}$ is an $N \times 1$ vector of errors with $\boldsymbol{\varepsilon} \sim \mathcal{N}(\boldsymbol{0}, \sigma^2 \boldsymbol{I})$.

Equation (4.2) includes spatial lags of both the endogenous variable and the explanatory variables on the right-hand side. This specification is called a Spatial Durbin Model

[9]The notation here follows Fischer (2011) and thus differs slightly from the one in Ertur and Koch (2007). The reason for this is to be precise and clear in the notation. In particular, by using the notation in Fischer (2011), having $\boldsymbol{X}$ denote two different matrices depending on context, is avoided.

(SDM) (Anselin, 1988, 111). By redefining $\boldsymbol{Z} = [\boldsymbol{\iota}_N \boldsymbol{X} \boldsymbol{W} \boldsymbol{X}]$ and $\boldsymbol{\delta} = [\beta_0, \boldsymbol{\beta}, \boldsymbol{\theta}]'$, it can be rewritten as (see LeSage and Pace, 2009, 46) $\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{Z}\boldsymbol{\delta} + \boldsymbol{\varepsilon}$, which is a spatial autoregressive (SAR) model.[10] In reduced form, the specification can be expressed as

$$\boldsymbol{y} = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{Z}\boldsymbol{\delta} + (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{\varepsilon} \tag{4.3}$$

and implies that the spatial lag of the endogenous variable and the error term are correlated so that the OLS parameter estimators are biased and inconsistent (Davidson and MacKinnon, 2004) and an alternative estimation strategy is thus necessary.

4.2 Estimation Strategy

Given these problems a different estimation strategy is necessary, and LeSage and Pace (2009, 45) note, with reference to Lee (2004), that maximum likelihood is a viable alternative.[11] Assuming that the errors are normally distributed, the specification the SAR model has the following log-likelihood function.

$$\begin{aligned} \ln L(\boldsymbol{y}; \boldsymbol{\delta}, \boldsymbol{\rho}, \sigma^2) = & -\frac{N}{2}\ln(2\pi) - \frac{N}{2}\ln(\sigma^2) + \ln|\boldsymbol{I} - \rho \boldsymbol{W}| \\ & - \frac{1}{2\sigma^2}\left[(\boldsymbol{I} - \rho \boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{\delta}\right]' \left[(\boldsymbol{I} - \rho \boldsymbol{W})\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{\delta}\right]. \end{aligned}$$

Finding the maximum for this function, requires calculating the partial derivatives with respect to all parameters, setting these necessary conditions equal to zero, and solving the system for the parameters. Instead, yielding identical results, this multivariate optimization problem can be reduced to a univariate optimization problem by concentrating the log-likelihood function with respect to the parameters $\boldsymbol{\delta}$ and σ^2 (LeSage and Pace, 2009, 47). This concentrated log-likelihood function depends, in addition to the sample

[10] The SAR model is nested in the SDM model and so, with the above rewriting, their likelihood functions coincide (LeSage and Pace, 2009, 46). Using the SAR model here is done to save on notation.

[11] Other approaches like instrumental variables (IV), generalized methods of moments (GMM) or Bayesian Markov Chain Monte Carlo (MCMC) might be alternatives (see Elhorst, 2010, 15).

data, only on the single parameter ρ and is given by

$$\ln L(\boldsymbol{y};\rho) = -\frac{N}{2}\ln(2\pi) + \ln|\boldsymbol{I}-\rho\boldsymbol{W}| - \frac{1}{2}\ln(\hat{\boldsymbol{e}}_O - \rho\hat{\boldsymbol{e}}_L)'(\hat{\boldsymbol{e}}_O - \rho\hat{\boldsymbol{e}}_L) \tag{4.4}$$

where $\hat{\boldsymbol{e}}_O$ are the estimated residuals from a regression of $\boldsymbol{y}$ on $\boldsymbol{Z}$ and $\hat{\boldsymbol{e}}_L$ those from a regression of $\boldsymbol{W}\boldsymbol{y}$ on $\boldsymbol{Z}$ (see Fischer, 2011, 427). Maximizing (4.4) yields a ML estimate $\hat{\rho}$, which can then be used to compute the ML estimates $\hat{\boldsymbol{\delta}}$ and $\hat{\sigma}^2$.

4.3 Model Interpretation

Due to the presence of the spatial lags $\boldsymbol{W}\boldsymbol{X}$ and $\boldsymbol{W}\boldsymbol{y}$ in equation (4.2), the interpretation of the parameters is a bit more complicated than in standard linear regression models, since feedback effects need to be taken into account. The partial derivatives of equation (4.2) with respect to e.g. the investment rate, are given by

$$\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{X}_1'} = (\boldsymbol{I}-\rho\boldsymbol{W})^{-1}(\boldsymbol{I}\beta_1 + \boldsymbol{W}\theta_1)\,. \tag{4.5}$$

This expression is an $N \times N$ matrix, representing the non-linear impacts on all countries resulting from a change in the investment rate in any country (Fischer, 2011). As LeSage and Pace (2009, 36) point out, in general, the impact of a change in an explanatory variable will not be identical across all observations. Therefore, they suggest a summary measure of these impacts. The row sums in the matrix in (4.5) represent the total impact to an observation, i.e. the impact of a change in the investment rate in all countries on steady-state income in region $i = 1 \ldots N$. The average of these row sums is then the average total impact to an observation. On the main diagonal of the matrix are the own partial derivatives or direct impacts from a change in the explanatory variable. These derivatives capture the effect of a change in, for example, the investment rate in country i on steady-state income in country i, and these impacts are summarized via averaging the entries on the diagonal of the matrix. LeSage and Pace (2009, 37) note that this corresponds, at least to a certain extent, to the typical interpretation of regression coefficients. Finally, the off-diagonal elements in the matrix are the cross-partial derivatives and represent the indirect (or spillover) impacts, which are again summarized by averaging the row sums of the respective matrix elements. In other words, this measure records the effect on the steady-state level income in country i resulting from a change in the investment rate in all countries except country i. Hence, the average indirect impact is given by the difference between the average total impact and the average direct impact.

5 Data, Estimation Results, and Robustness Checks

5.1 Data

The main data source for the replication exercise is PWT 6.1, while for the robustness checks PWT 6.2 and 7.1 are used.[12] As in Ertur and Koch (2007, 1042), the initial sample covers the 91 countries of the non-oil sample used by Mankiw et al. (1992), for which data is available over the period 1960-1995. In contrast to the theoretical model, empirically GDP per capita and GDP per worker are not, in fact, identical. Hence, the dependent variable, y, is real GDP per worker (variable *rgdpwok* in PWT). The investment rate, s, is the real share of investment in real GDP (variable *ki* in PWT), averaged over the respective years. For the average growth rate of workers, n, no directly corresponding variable is available in PWT. A number for the size of the working-age population can be recovered by noting that series for real GDP per capita and population are available so that the number of workers can be calculated by multiplying real GDP per capita (*rgdch* in PWT) by the size of the population (*pop* in PWT) and dividing the result by the value of real GDP per worker. The average growth rate of the working-age population is then calculated as an approximation (though this is not stated explicitly in Ertur and Koch

[12] A more recent version (8.0) of the Penn World Table is also available. This data will however not be used in this analysis, as it lacks data on the real share of investment in real GDP. See Table A3 in the file "variable correspondence" under `http://www.rug.nl/research/ggdc/data/pwt/pwt-8.0`.

(2007)) by taking the natural logarithm of the difference between the number of workers in 1995 and 1960 divided by 35.

For the construction of the interaction matrices, the general assumptions made in Subsection 3 are valid. An additional important point is that the weights in these matrices should be exogenous (Ertur and Koch, 2007, 1042), making geographic and genetic distance ideal candidates.[13] The matrices that are based on spatial distances use as weights the great circle distances, d_{ij}, between country capitals i and j. There is however some scope in pinning down the latitude and longitude of a capital, and Ertur and Koch provide no information for their source of this data. In this paper, in all calculations that rely on latitude and longitude, the coordinates are taken from the CIA's World Factbook (Central Intelligence Agency, 2013). As a final step, the weights for the interaction matrices are given by $w_{ij}(1) = w^*_{ij}(1)/\sum_j w^*_{ij}(1)$ as well as $w_{ij}(2) = w^*_{ij}(2)/\sum_j w^*_{ij}(2)$, and are based on the following functional forms

$$w^*_{ij}(1) = \begin{cases} 0 & \text{if } i = j \\ d_{ij}^{-2} & \text{otherwise} \end{cases} \quad \text{and} \quad w^*_{ij}(2) = \begin{cases} 0 & \text{if } i = j \\ e^{-2d_{ij}} & \text{otherwise} \end{cases}. \tag{5.1}$$

Considering the inverse of the squared distance in equation (5.1) reflects a gravity function (Ertur and Koch, 2007, 1042), implying that the effect of the spatial externalities weakens more than proportionally with distance (see e.g. Keller, 2002). The spatial weight matrix based on the first set of weights in equation (5.1) is called $\boldsymbol{W_1}$ and the one based on the second set, which Ertur and Koch (2007) employ as a robustness check, is $\boldsymbol{W_2}$.

The data on genetic distance is taken from the data set of Spolaore and Wacziarg (2009), who rely on data assembled by Cavalli-Sforza et al. (1994). Following the construction of the original weight matrices based on geographic distance, the functional form in equation (5.1) has been chosen for the interaction matrix $\boldsymbol{W_3}$ based on F_{ST} genetic distances, too.

[13] Another interesting variable on which to base the weights would be, for example, a measure of technological proximity between countries. However, this measure could not be considered exogenous to the model for the sample period considered in this paper.

5.2 Results – Interaction Matrix Based on Geographic Distance

Estimation results are presented in Table 5.1.[14] The first two columns replicate the results from Table 1 in Ertur and Koch (2007) and serve as a benchmark.[15] Column 1 shows in the upper half estimates of the standard Solow model by ordinary least squares (OLS). The estimated coefficients on the investment rate and on the population growth rate have the signs expected from the theoretic model and in addition are highly significant. In the lower half, this model is estimated with the restriction $\beta_1 = -\beta_2$ imposed, which is rejected by a Wald test ($p = 0.038$). Also, the implied value for the capital share, $\alpha = 0.58$, is too high compared to empirical estimates (Gollin, 2002), and Moran's I test indicates spatial autocorrelation in the error term. Based on these results, Ertur and Koch (2007, 1046) conclude that the standard model is misspecified, as it fails to account for physical capital externalities and technological interdependence between countries.

Column 2 shows that the estimation results support the implications of the spatially augmented model. All coefficients have the signs predicted from theory (see equation (4.1)), even though, for instance, the estimated coefficient associated with the spatial lag of the population growth rate is insignificant ($p = 0.479$). The likelihood ratio test does not reject the joint theoretical restriction $\beta_1 + \beta_2 = 0$ and $\theta_1 + \theta_2 = 0$, as $p = 0.419$, which supports the validity of the spatially augmented model. In addition, the (significant) implied value for the capital share of income is $\alpha = 0.284$ and thus much closer to empirical estimates. Furthermore, the parameter ϕ, reflecting physical capital externalities, is positive and significant at the 10%-level. Also, the implied value for γ, which gauges the degree of technological interdependence among countries is positive and highly significant, implying that this characteristic indeed needs to be taken into

[14]All estimations have been carried out in Matlab using the Spatial Econometrics Toolbox by LeSage, which is publicly available under: `http://www.spatial-econometrics.com/`.

[15]Note that since the analysis here is based on the geographic coordinates from the World Factbook, which differ in some cases slightly from the coordinates used by Ertur and Koch (2007), the values for the Morans's I test in the unrestricted and restricted versions of the standard Solow model in column 1 as well as the values for the spatially augmented Solow model in column 2 are slightly different. Qualitatively the results are not affected. Also, there is a slight mistake in Ertur and Koch's Table I, as the values for the Moran's I test in the unrestricted Solow model belongs to the restricted Solow model and vice versa.

account in growth models, as economies cannot be considered as independent observations (Fischer, 2011, 432). Finally, the value of $\alpha + \phi/(1-\gamma)$ is below 1, implying that the externalities are not strong enough to lead to endogenous growth (Ertur and Koch, 2007, 1048). In sum, the estimation results provide rather strong support for the model.

The next columns assess the sensitivity of these results, when moving from PWT 6.1 to version 6.2 and 7.1. Due to missing data in PWT 6.2, the sample size needs to be reduced to 83 countries in the estimations based on this data source. In order to obtain estimation results for a balanced sample across all three versions of the PWT considered in this paper, columns 3 and 4 first show estimation results for the 83-country sample with data from PWT 6.1. For the standard model, the results are virtually identical (column 3) to those from the full sample. However, dropping these 8 observations from the sample affects the results in the spatial model. The implied values for α and ϕ are comparable in size to the full sample with 91 countries, but they are now insignificant.

Columns 5 and 6 change the data source to PWT 6.2. In column 5, the estimation results are in line with those from columns 1 and 3. The only exception is that, for this data source, the restriction $\beta_1 = -\beta_2$ is not rejected, suggesting a good fit between the model and the data, except that the implied value for α is still too high. For the unconstrained estimation of the spatial model, column 6 shows that, compared to columns 1 and 3, the coefficient for the population growth rate still has the sign implied by theory, but is now insignificant ($p = 0.347$). The results from the estimation with the joint parameter restriction applied, indicate that, as for the results for the 83-country sample with data from PWT 6.1, the implied share of capital income and the parameter for the physical capital externalities are insignificant (p-values of 0.403 and 0.213, respectively). Hence, changing the data source from PWT 6.1 to 6.2, suggests that, while many results (e.g. the implied value of γ or the test of the joint restriction) are not sensitive to this change, the original results by Ertur and Koch (2007) concerning α and ϕ are not robust.

More drastic changes to the benchmark results are visible when moving to PWT 7.1 in

Table 5.1: Estimation Results for the Standard and Spatially Augmented Solow Model According to Three Different Versions of the PWT Based on Interaction Matrix $\boldsymbol{W}_1$ (Geographic Distance).

Data set	PWT 6.1				PWT 6.2		PWT 7.1	
Model	Stand.	Spatial	Stand.	Spatial	Stand.	Spatial	Stand.	Spatial
Number of observations	91	91	83	83	83	83	83	83
Unconstrained estimation:								
Constant	4.651	0.886	4.609	0.518	7.130	2.780	2.976	1.828
	(0.010)	(0.635)	(0.017)	(0.796)	(0.000)	(0.181)	(0.189)	(0.399)
$\ln s_i$	1.276	0.836	1.234	0.789	1.319	0.876	1.697	0.944
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(n_i + 0.05)$	−2.709	−1.538	−2.701	−1.449	−1.835	−0.689	−3.428	−1.441
	(0.000)	(0.006)	(0.000)	(0.021)	(0.008)	(0.347)	(0.000)	(0.081)
$\boldsymbol{W} \ln s_j$	—	−0.347	—	−0.314	—	−0.160	—	0.710
		(0.057)		(0.137)		(0.514)		(0.110)
$\boldsymbol{W} \ln(n_j + 0.05)$	—	0.591	—	0.343	—	−0.191	—	−0.298
		(0.479)		(0.705)		(0.843)		(0.793)
$\boldsymbol{W} \ln y_j$	—	0.742	—	0.732	—	0.608	—	0.595
		(0.000)		(0.000)		(0.000)		(0.000)
Moran's I (LM) test	0.432	—	0.397	—	0.346	—	0.389	—
	(0.000)		(0.000)		(0.000)		(0.000)	
Constrained estimation:								
Constant	8.375	2.118	8.407	2.220	8.465	3.158	7.321	1.939
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
$\ln s_i - \ln n_i$	1.379	0.855	1.354	0.813	1.356	0.871	1.904	0.958
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\boldsymbol{W}[\ln s_j - \ln(n_j + 0.05)]$	—	−0.292	—	−0.230	—	−0.149	—	0.692
		(0.098)		(0.270)		(0.527)		(0.109)
$\boldsymbol{W} \ln y_j$	—	0.735	—	0.721	—	0.613	—	0.608
		(0.000)		(0.000)		(0.000)		(0.000)
Moran's I (LM) test	0.415	—	0.4397	—	0.342	—	0.377	—
	(0.000)		(0.000)		(0.000)		(0.000)	
Test of restriction	4.427	1.738	4.066	1.474	0.514	0.127	3.805	0.358
	(0.038)	(0.419)	(0.047)	(0.479)	(0.476)	(0.938)	(0.055)	(0.836)
Implied α	0.580	0.284	0.575	0.242	0.576	0.196	0.656	8.261
	(0.000)	(0.012)	(0.000)	(0.120)	(0.000)	(0.403)	(0.000)	(0.852)
Implied ϕ	—	0.177	—	0.206	—	0.270	—	−7.772
		(0.082)		(0.139)		(0.213)		(0.861)
Implied γ	—	0.554	—	0.525	—	0.408	—	−0.043
		(0.000)		(0.000)		(0.009)		(0.868)
$\alpha + \frac{\phi}{1-\gamma}$	—	0.680	—	0.676	—	0.651	—	0.808
		(0.000)		(0.000)		(0.000)		(0.000)

Note: p-values are given in parentheses. For the standard Solow model the restriction is tested with the Wald test and for the spatially augmented model with the likelihood ratio (LR) test.

columns 7 and 8. For the standard model, the signs of the coefficient estimates have the expected signs, and Moran's I test indicates misspecification with respect to spatial correlation in the error term. As for results for the PWT 6.1 sample, the parameter restriction $\beta_1 = -\beta_2$ is rejected. However, in the spatially augmented model in column

8, the constrained estimation implies an implausibly large share of capital income with an estimated value for α of 8.261 (although this value is not significant with $p = 0.852$). Moreover, the value for the physical capital externalities is now negative, but also not significant ($p = 0.861$). The same holds for the parameter measuring technological interdependence. These estimates imply that using a more recent data source leads to drastic changes in the empirical results compared to the benchmark results.[16]

It needs to be kept in mind though that,in addition to the results in Table 5.1, the model's interpretation relies on the calculation of the direct and indirect effects. The results for these impacts are presented in Table 5.2 for all four samples considered in this paper. In the paper by Ertur and Koch only the direct effects are reported (though without any reference to the significance of these estimates). Here, a richer analysis is presented by also reporting estimates for the indirect and total impacts of changes in the exogenous variables. Concerning the direct impacts, the results show that across all four samples an increase in the investment rate in physical capital is approximately comparable in size and significance. The estimated coefficients are highly significant and imply, due to the log-specification of the model, that a 10% increase in the investment rate would result in an increase in per-capita income between 8.6% and 11.6%. The results for the indirect impacts of changes in the investment rate, resulting from spatial spillovers, differ however across the samples. Whereas these impacts are comparable in size for the first three samples, the impact is only significant for the PWT 6.2 sample at the 10%-level. For the PWT 7.1 sample, this effect has tripled in size compared to the other estimates and is significant at the 1%-level. These findings indicate again that the results in Ertur and Koch are not robust with respect to changing to more recent versions of the PWT. It is however interesting to note that, at least for the first three samples, the direct and

[16]That changing the data source from e.g. PWT version 6.1 or 6.2 to 7.1 can lead to different results in models similar to the one considered here, has also been pointed out by Johnson et al. (2013, 270). They find that in the Solow model augmented with human capital by Mankiw et al. (1992), the coefficient on the investment share is reduced in size close to zero, when the estimation is based on a more recent version of the PWT (7.0 in their case). This finding is attributed to the investment series being more variable in this version of the PWT due to unclear reasons (Johnson et al., 2013, 270).

Table 5.2: Estimation Results for the Direct, Indirect and Total Impacts According to Three Different Versions of the PWT Based on Interaction Matrix $\boldsymbol{W_1}$ (Geographic Distance).

Data set	PWT 6.1		PWT 6.2	PWT 7.1
Number of observations	91	83	83	83
Direct impacts:				
$\ln s_i$	0.916	0.859	0.941	1.158
	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(n_i + 0.05)$	−1.693	−1.636	−0.793	−1.635
	(0.005)	(0.013)	(0.269)	(0.043)
Indirect impacts:				
$\boldsymbol{W} \ln s_j$	1.030	0.960	0.915	3.012
	(0.118)	(0.198)	(0.057)	(0.004)
$\boldsymbol{W} \ln(n_j + 0.05)$	−2.008	−2.559	−1.458	−2.709
	(0.484)	(0.423)	(0.476)	(0.218)
Total impacts:				
$\ln s_i + \boldsymbol{W} \ln s_j$	1.945	1.820	1.856	4.170
	(0.007)	(0.023)	(0.000)	(0.000)
$\ln(n_i + 0.05) + \boldsymbol{W} \ln(n_j + 0.05)$	−3.701	−4.196	−2.251	−4.343
	(0.230)	(0.220)	(0.294)	(0.054)

Note: p-values are given in parentheses. These were constructed using a set of 500,000 random draws from the estimation.

indirect impacts from the investment rate contribute both approximately 50% to the total impact of this variable. Table 5.2 also shows that the results concerning the impacts of the population growth rate are not robust across samples.

Before turning to the estimation results for the interaction matrix based on genetic distance, it should be remembered that Ertur and Koch have also employed an interaction matrix based on the second specification in (5.1) to assess the sensitivity of their results. Also in this case, the original results, in general, are not robust across the different samples.[17,18]

[17] Detailed results are available on request from the author.

[18] Concerning interaction matrix $\boldsymbol{W_2}$, a comment needs to be made. This matrix does not seem to correspond exactly to the specification Ertur and Koch (2007) actually use in their analysis. From the Matlab code on the article's website, it is clear that their estimation results are obtained by dividing the geographic distances d_{ij} by $1,000$. A reason for this transformation is not given however, and it turns out that the estimation results are highly sensitive to this alternative specification. For instance, not dividing the distances by $1,000$, the estimation results imply highly significant negative values for the parameters ϕ and γ, and α increases to an unreasonably, but highly significant value of 90% ($p = 0.000$). With respect to the impact estimates, the values for the direct and total impacts are approximately comparable across both specifications, the indirect effects, however, turn from being not significant in the specification as implemented by Ertur and Koch to being strongly significant in the specification as claimed in the article. Again, detailed results are available on request.

5.3 Results – Interaction Matrix Based on Genetic Distance

This subsection presents the estimation results when the interaction matrix is based on genetic distance. The general specification of the weights is given by the first specification in (5.1), and the analyses use F_{ST} distance.[19] As the results for the standard model do not depend on the interaction matrix, Table 5.3 shows only the results from the estimation of the spatial Durbin model.[20] Column 1 provides the results for the full sample of 91 countries for data taken from PWT 6.1. In contrast to the benchmark, i.e. the original results in Ertur and Koch, the estimates based on genetic distance show, for instance, that the coefficient associated with the spatial lag of the investment rate is now positive and highly significant. The results for the constrained estimation also differ from the ones with an interaction matrix using geographic distance, as the implied value for α is now implausibly large and highly significant. Moreover, γ, measuring the degree of technological interdependence is now negative and marginally significant at the 10%-level, which seems implausible.[21] Similar results are also obtained for the other samples: When using data from PWT 7.1 for instance, the implied value for the capital share of income in column 4 actually turns negative (although the p-value is 0.803). In neither sample, based on a likelihood ratio test, the joint parameter restriction $\beta_1 + \beta_2 = 0$ and $\theta_1+\theta_2 = 0$ is rejected though. Despite these results from the estimation of the constrained model across the four samples, the impact estimates in Table 5.4, which are calculated from the unconstrained estimation results, will be briefly discussed. Across all samples, the estimates for the direct impact of a change in the investment rate on steady-state per capita income are comparable to the results for the model with interaction matrix $\boldsymbol{W_1}$. One important difference to the results in Table 5.2 concerns the spillovers from a change in the investment rate for the full sample of 91 countries. The estimated effects are now

[19] The estimation results based on Nei's distance are comparable to the ones in Tables 5.3 and 5.4. Detailed results are available from the author on request.

[20] It is worth pointing out however, that in all samples the standard model continues to be misspecified, based on the values for Moran's I with matrix $\boldsymbol{W_3}$ (p-values are 0.000 in all four tests).

[21] The implied values for α, ϕ, and γ are of approximately similar size in the estimation based on Nei's distance for this sample, though neither value is significant at the 10%-level. This is the exception from the claim about comparable results for both measures of genetic distance made in Footnote 19.

Table 5.3: Estimation Results for the Spatial Durbin Model According to Three Different Versions of the PWT based on Interaction Matrix $\boldsymbol{W_3}$ (Genetic Distance F_{ST}).

Data set	PWT 6.1		PWT 6.2	PWT 7.1
Number of observations	91	83	83	83
Unconstrained estimation:				
Constant	8.654	8.246	5.941	−1.932
	(0.001)	(0.000)	(0.011)	(0.423)
$\ln s_i$	0.820	0.945	0.888	0.972
	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(n_i + 0.05)$	−1.034	−0.871	−0.148	−0.930
	(0.054)	(0.099)	(0.790)	(0.153)
$\boldsymbol{W} \ln s_j$	0.901	0.665	0.725	−0.009
	(0.000)	(0.001)	(0.002)	(0.983)
$\boldsymbol{W} \ln(n_j + 0.05)$	0.651	0.431	−1.625	−1.912
	(0.500)	(0.632)	(0.096)	(0.078)
$\boldsymbol{W} \ln y_j$	0.322	0.327	0.198	0.556
	(0.006)	(0.002)	(0.128)	(0.000)
Constrained estimation:				
Constant	5.520	5.452	6.013	2.452
	(0.000)	(0.000)	(0.000)	(0.000)
$\ln s_i - \ln n_i$	0.785	0.856	0.870	0.996
	(0.000)	(0.000)	(0.000)	(0.000)
$\boldsymbol{W}[\ln s_j - \ln(n_j + 0.05)]$	0.850	0.653	0.655	0.130
	(0.000)	(0.001)	(0.003)	(0.743)
$\boldsymbol{W} \ln y_j$	0.280	0.296	0.245	0.605
	(0.019)	(0.005)	(0.045)	(0.000)
Test of restriction	2.450	1.949	1.862	3.708
	(0.294)	(0.377)	(0.394)	(0.157)
Implied α	1.491	1.830	1.598	−0.273
	(0.003)	(0.052)	(0.038)	(0.803)
Implied ϕ	−1.052	−1.360	−1.133	0.772
	(0.039)	(0.155)	(0.147)	(0.474)
Implied γ	−0.319	−0.189	−0.219	0.238
	(0.098)	(0.196)	(0.212)	(0.288)
$\alpha + \frac{\phi}{1-\gamma}$	0.694	0.686	0.669	0.740
	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values are given in parentheses. The restriction is tested with the likelihood ratio (LR) test.

highly significant and imply that a change of 1% in the investment rate in all countries except country i would result in an increase of approximately 1.7% in per-capita income in country i. Another interesting result is that these spillovers are not significant in the sample for PWT 7.1, whereas the reverse holds for this sample in the estimation with geographic distance. There this estimate is not only highly significant, but also large in size. Table 5.4 furthermore clearly shows that the impacts with respect to the population growth rate are highly sensitive to the particular version of the PWT.

Table 5.4: Estimation Results for the Direct, Indirect and Total Impacts According to Three Different Versions of the PWT Based on Interaction Matrix $\boldsymbol{W_3}$ (Genetic Distance F_{ST}).

Data set	PWT 6.1		PWT 6.2	PWT 7.1
Number of observations	91	83	83	83
Direct impacts:				
$\ln s_i$	0.887	1.004	0.918	1.035
	(0.000)	(0.000)	(0.011)	(0.000)
$\ln(n_i + 0.05)$	−1.009	−0.856	−0.198	−1.229
	(0.058)	(0.101)	(0.722)	(0.060)
Indirect impacts:				
$\boldsymbol{W} \ln s_j$	1.673	1.401	1.098	1.116
	(0.000)	(0.000)	(0.000)	(0.156)
$\boldsymbol{W} \ln(n_j + 0.05)$	0.506	0.260	−1.996	−5.246
	(0.701)	(0.830)	(0.062)	(0.001)
Total impacts:				
$\ln s_i + \boldsymbol{W} \ln s_j$	2.560	2.405	2.015	2.151
	(0.000)	(0.000)	(0.000)	(0.012)
$\ln(n_i + 0.05) + \boldsymbol{W} \ln(n_j + 0.05)$	−0.503	−0.560	−2.193	−6.475
	(0.707)	(0.627)	(0.035)	(0.003)

Note: p-values are given in parentheses. These were constructed using a set of 500,000 random draws from the estimation.

6 Conclusion

This paper has presented the growth model with technological interdependence among countries developed by Ertur and Koch (2007) and subjected their empirical results to a series of robustness checks. In contrast to the original specification with an interaction matrix based on geographic distance, this paper has used data on genetic distance from Spolaore and Wacziarg (2009) to construct an alternative interaction matrix. Furthermore, additional robustness checks have been conducted to assess the sensitivity of the original results across different versions of the Penn World Table for the same period and the same set of countries. The analyses show that the original results by Ertur and Koch are highly sensitive to the version of the PWT. They estimate, for instance, an implied capital share of income slightly below 30%, but this result is not robust, when estimating the model for PWT 6.2 and 7.1. Furthermore, whereas Ertur and Koch only provide estimates of the direct impacts associated with changes in the exogenous variables, in this article values for the indirect and total impacts have been calculated as well. The results again indicate non-robustness across different versions of the PWT, as, for example, the indirect impact (or spillover) associated with changes in the investment rate on per capita income is not significant in the PWT 6.1 sample, but significant in PWT 6.2 and 7.1. Results have also been shown to be highly sensitive to the precise specification of the weights in the interaction matrix based on geographical distance.

Concerning genetic distance, this paper finds that, whereas in the original model indirect spillovers from capital investment were insignificant in the PWT 6.1 sample, with genetic distance, these spillovers now have a significant effect on steady-state income per worker. However, the model with an interaction matrix based on genetic distance implies an implausibly large capital share of income. It can thus be stated that the empirical results in Ertur and Koch are sensitive to the measure on which the weights in the interaction matrix are based (geographic or genetic distance) as well as to the concrete specification of the weights in the interaction matrix.

In this paper, as in Fischer (2011), only level regressions have been addressed. Future work will also investigate the sensitivity of the estimates for the growth regressions in Ertur and Koch (2007), as well as the impact of human capital. Results from Ertur and Koch (2006) suggest that this factor is not related to growth within this framework. However, as the results in this paper clearly demonstrate, that this holds across different versions of the PWT is not necessarily the case. It should be pointed out that an endogenous version of the model framework exists as well (Ertur and Koch, 2011), which, for a different set of countries, a different time period, and different interaction matrices, provides empirical support, based in part on data from PWT 6.2, in favor of the endogenous version. But again, this is no guarantee that this necessarily needs to hold across different versions of the PWT. Robustness should be assessed for this finding as well. As this paper has also demonstrated the sensitivity of the results to the choice of interaction matrix, further research will be devoted to this issue. In particular, Bayesian Model Averaging will be used to address the uncertainty concerning the specification of the interaction matrix in this model.

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