Human Capital, Technology Diffusion, and Total Factor Productivity Growth in Regions

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Abstract

Until recently, the geographical coverage of data sets on the sub-national level was usually rather limited and hardly included regions of less developed economies. Considering new regional data collection, this has started to change, thereby paving the way for new regional growth analysis. Employing such an extensive data set, this paper investigates the role of human capital and technology spillovers on regional total factor productivity growth for 569 regions in 30 countries. Nonlinearities in the effects of the explanatory variables as well as spatial spillovers caused by a spatial autoregressive process of the dependent variable and the explanatory variables are considered in the estimation model. The findings confirm a robust direct impact of technological catch-up on regional total factor productivity growth, where the catch-up speed increases with increasing levels of human capital. This supports the common hypothesis of an educated labor force enhancing technology adoption from abroad. Furthermore, positive spatial spillovers of technology levels are observed.

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1 Introduction

Recent literature and data collection by Gennaioli, La Porta, López-de Silanes & Shleifer (2013, 2014), Lessmann (2014) and Mitton (2016) have paved the way for new regional growth analysis. Until then, the geographical coverage of data sets on the sub-national level was usually rather small, biased towards industrialized economies and hardly included developing countries. Considering the contributions by the above mentioned authors, this has begun to change. Employing the extensive data set by Gennaioli et al. (2014), the present paper investigates the role of human capital and technology spillovers on regional total factor productivity growth for 569 regions in 30 countries (including 15 non-OECD countries). The general dynamic of total factor productivity is defined according to the model put forward by Benhabib & Spiegel (1994). Non-linearities in the effects of the explanatory variables as well as spatial spillovers caused by a spatial autoregressive process in the dependent and independent variables are taken into account.

According to basic neoclassical growth theory, short-run income per capita growth is determined by physical capital accumulation, while the long-run growth rate is solely dependent on the growth rate of technology, which is exogenously determined. In an influential paper, Mankiw, Romer & Weil (1992) augment the neoclassical growth model by including human capital as an additional production factor. Consequently, higher investment in human capital has a positive effect on the level of income per capita and also leads to a temporary increase in its growth rate. The long-run growth rate of income per capita, however, remains unaffected and is again determined by the exogenous growth rate of technology.

Benhabib & Spiegel (1994) offer an alternative to this approach. Consistent with Romer (1990), human capital enters the model as a prerequisite for domestic innovation, thereby influencing the growth rate of technology directly. Moreover, human capital is assumed to be a determinant of technology diffusion as in Nelson & Phelps (1966). The general presumption is that an educated labor force is not only better at creating its own technology, but also at implementing and adopting new technologies from abroad. Consequently, in the model by Benhabib & Spiegel (1994) the growth rate of technology and therefore the long-run growth rate of income per capita, is not exogenous but instead determined by the stock level of human capital and its interaction with backwardness.

Referring to existing empirical evidence for the effect of human capital on regional income growth, Gennaioli et al. (2014) find a positive and significant coefficient estimate attached to the variable average years of schooling. They compute panel regressions for a sample of 1,528 regions, including geographical variables and a specification with country fixed effects in an effort to control for the large cross country differences in productivity, institutions and technology. The positive effect of years of schooling holds in both cases, with and without country fixed effects. Their results are in line with with previous cross-sectional evidence suggesting that differences in education explain by far the largest share of differences in per capita incomes across sub-national regions (Gennaioli et al., 2013).

Concerning a smaller geographical coverage, there is a significant quantity of other studies addressing the impact of human capital on regional income growth. Crespo Cuaresma et al. (2014) for example, investigate the determinants of economic growth in European regions using Bayesian Model Averaging methods. Their results show that human capital, measured as the population share of highly educated workers, a proxy for income convergence and a capital city dummy are the only three out of 54 variables with a robust impact on growth of income per capita. The positive effect of human capital remains robust when controlling for fixed country effects, even though the parameter is not as well estimated as in the specification without country fixed effects. Crespo Cuaresma et al. (2014) also incorporate the possibility of spatial dependencies. They find that their robust parameter results are equally present in a spatial setting. Fischer & LeSage (2008), who also apply Baysian Model Averaging methods for European regions in a spatial model setting, similarily find a positive direct impact of human capital on growth, but the total impact is not significantly different from zero. They interpret this outcome by arguing that increasing human capital across all regions would likely have no effect on the growth rate of a typical region because no relative regional advantages can be exploited. Basile (2008) tests a semiparametric spatial model and detects non-linearities as well as spatial spillovers related to the effect of the secondary school enrollment ratio on regional income growth.

With regard to technology diffusion, Abreu et al. (2004) identify two broad schools of thought in the literature. The first focuses on the capacity of technological catch-up, i.e. the ability to adopt foreign technology in the domestic market. It is based on the assumption of a common pool of technological knowledge to which all countries have access, such that the only constraint to adoption is a country's ability to understand and implement the new technology. The model by Nelson & Phelps (1966) represents an example of this view. In this case, a country's adoption of new technologies depends on its human capital, representing the absorptive capacity, and on the gap between the current technology present in this country and the cutting-edge technology. At the country level, prominent empirical evidence supporting this view is given by Benhabib & Spiegel (1994) and Benhabib & Spiegel (2005). There is also some evidence for a significant impact of technology adoption when regions are considered as the units of observation (e.g. Badinger & Tondl, 2003; Fleisher et al., 2010).

According to Abreu et al. (2004), the second view on technology diffusion stresses the importance of bilateral ties. Countries are endowed with different stocks of knowledge capital and diffusion can occur over several channels such as flows of goods, services, labor or capital. The intensity of these bilateral ties might be determined by geographical distance. Ertur & Koch (2007) provide a theoretical growth model which considers technological interdependence among economies working through spatial externalities. Fischer (2011) extends their model by to a Mankiw, Romer & Weil (1992) model setting. The empirical evidence on spatial spillovers of technology is vast. Keller (2001) estimates the importance of geographic distance for technology diffusion and whether international trade, foreign direct investment, and language skills serve as important channels of diffusion. Other studies measure knowledge spillovers by patent activity. Eaton & Kortum (1996) investigate technology diffusion and patent activity in OECD countries and show that patent citations decline with geographical distance. They further conclude that once geographical distance is taken into account, import composition may not matter much. Fischer et al. (2009) proxy regional stocks of knowledge capital as regional patent stocks and study their impact on total factor productivity. They find that productivity effects of knowledge spillovers increase with spatial proximity. LeSage & Parent (2008) include the possibility of industry-specific technological linkages in addition to the geographical dimension of knowledge spillovers arising from patenting activity.

From this discussion it follows that there is considerable evidence suggesting that technology diffusion may have a spatial dimension and that country characteristics such as the stock of human capital might play an important role for technological catch-up. By imposing a structure of spatial dependencies on the model by Benhabib & Spiegel (1994), both approaches are combined. Examples of studies that are based on the technology diffusion model outlined by Benhabib & Spiegel (1994) and that control for spatial dependencies are Abreu et al. (2004) for countries and Fleisher et al. (2010) for the regions of China. The latter do not account for spatial autocorrelation explicitly, but discount technological catch-up by geographical distance. Using the data set from Gennaioli et al. (2014), this paper will test the model for a much larger geographical coverage of 569 regions. This should give some additional insight into the process of regional technology diffusion and into the role of human capital as a determinant of total factor productivity growth, also when considering regions of less developed economies.

The findings confirm significantly positive direct impacts of technological catch-up and human capital on regional TFP growth. Notably, the hypothesis of human capital supporting technological progress is supported by the results. Moreover, a negative average indirect impact of the technology gap is observed, which is interpreted as positive spatial spillovers of technology *levels*. In contrast, spatial autocorrelation of technology *growth* is only significant when not controlling for country-specific effects. The results are robust to changes in the set of explanatory variables, to different spatial diffusion patterns and as well when outliers are excluded from the sample.

The paper is organized as follows. Section 2 presents the model of technology diffusion by Benhabib & Spiegel (1994) and embeds it in a spatial econometric setting. Section 3 describes the data. Section 4 presents the results of estimating a linear regression model and a Spatial Durbin Model. Following this, it checks the robustness of the results to variations in the explanatory variables and in the spatial weight matrix. Section 5 draws conclusions from the foregoing findings.

2 The Empirical Model

2.1 The Model by Benhabib & Spiegel (1994)

The model used in this paper is based on the model of technology diffusion by Benhabib & Spiegel (1994), but is modified in such a way that a region's technology growth depends also on the technology growth of other regions. Assuming that the growth rate of technology for region i over time follows the model by Benhabib & Spiegel (1994), it is defined as

$$\frac{\dot{A}_i(t)}{A_i(t)} = g(H_i(t)) + c(H_i(t))\frac{A_m(t) - A_i(t)}{A_i(t)}, \qquad i = 1, ..., N \tag{1}$$

where $A_i(t)$ is the level of technology in region i at time t, $H_i(t)$ is its exogenous stock of human capital, and $A_m(t)$ is the level of technology in the region with the highest level of technology (technology leader) at time t. $g(H_i(t))$ and $c(H_i(t))$ are assumed to be non-decreasing functions of H_i. As outlined above, technological progress is considered to depend on the stock of human capital and on technology adoption from abroad. The term $g(H_i(t))$ represents domestic innovation. It is the endogenous and region specific technological growth rate driven by human capital. The technology gap between leader region m and region i is represented by the term $\frac{A_m(t)-A_i(t)}{A_i(t)}$. $c(H_i(t))$ is the speed at which the technology gap closes during each period of time and is a function of region i's human capital stock. The model implies that if the ranking of $g(H_i(t))$ across regions does not change, and if $g(H_m(t)) > g(H_i(t))$, then in finite time there will be an equilibrium where all regions grow at $g(H_m(t))$, the domestic innovation of the leader region m[1]. Note that the model implicitly presumes that a region only adopts technology from the technology leader. Supposing that a region might also benefit from technology spillovers of other regions, a spatial model setting should be employed.

2.2 Econometric Model Specification: Spatial Durbin Model

To investigate the growth rate of total factor productivity (TFP)[2], a general spatial autoregressive model will be used. In addition to the theoretical background and empirical evidence on spatial knowledge spillovers presented in section 1, the mere fact of working with regional data encourages the use of a specification which includes the possibility of spatial dependencies (LeSage & Pace, 2010). The Spatial Durbin Model (SDM) takes the form

$$\boldsymbol{y} = \alpha\boldsymbol{\iota}_N + \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\epsilon}, \qquad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \sigma^2\boldsymbol{I}_N) \tag{2}$$

[1]If $g(H_i(t)) > g(H_m(t))$, then region i will finally overtake the technology leader m.
[2]The terms "total factor productivity" and "technology" are used interchangeably.

where N is the number of regions, $\boldsymbol{y}$ is an N-dimensional vector of regional TFP growth rates, α is the scalar for the intercept, $\boldsymbol{\iota}_N$ is an N-dimensional vector of ones, ρ is the spatial autocorrelation coefficient where $-1 < \rho < 1$, $\boldsymbol{W}$ is an N-by-N row-standardized spatial weight matrix, $\boldsymbol{X}$ is the N-by-K matrix of K explanatory variables, $\boldsymbol{\beta}$ is a K-dimensional vector of coefficients corresponding to the explanatory variables, and $\boldsymbol{\theta}$ is a K-dimensional vector of coefficients for the spatially lagged explanatory variables. The error term $\boldsymbol{\varepsilon}$ is assumed to be normally distributed with zero mean and diagonal variance-covariance $\sigma^2\boldsymbol{I}_N$.

The spatial weight matrix $\boldsymbol{W}$ imposes a structure on the spatial dependencies. It is non-stochastic and non-negative. If observation i and j are related (i.e. are considered to be neighbors), then the element $W_{ij} > 0$ for $i \neq j$ $(i = 1, ..., N)$ and $W_{ij} = 0$ otherwise. Also the main diagonal elements are set to zero, since a region is not a neighbor to itself. Furthermore, $\boldsymbol{W}$ is row-standardized, such that the i^{th} element of the spatial lag vector $\boldsymbol{Wy}$ is a linear combination of growth rates from neighboring regions of i. In this paper, neighborhood will be defined primarily according to the k-nearest principle, implying that $W_{ij} > 0$ if region j is among the k nearest regions of i. Prior to row-standardization, $W_{ij} = 1$ if j is a neighboring region of i. In the light of the high number of regions in this particular data set and the large variability in their sizes, it is arguably more sensible to use the k-nearest specification in comparison to other distance-based measures of neighborhood. However, a robustness check for a distance-decay matrix will be computed when analyzing the estimation results.

The matrix $\boldsymbol{X}$ of explanatory variables is specified as $\boldsymbol{X} = [\boldsymbol{h} \quad \boldsymbol{a} \quad \boldsymbol{h} \circ \boldsymbol{a}]$. The vector $\boldsymbol{h}$ consists of the regions' human capital stocks. The vector $\boldsymbol{a}$ represents the technology gap, with a typical element in row i defined as $a_i = \frac{A_m}{Ai}$, where A_m and A_i are given according to the Benhabib & Spiegel (1994) model (see equation 1). Potential interaction effects of the main terms $\boldsymbol{h}$ and $\boldsymbol{a}$ are denoted by $\circ$, representing the Hadamard product of element-wise multiplication. Note that the definition of $\boldsymbol{X}$ is based on the Benhabib & Spiegel (1994) model, since equation 1 can be written as $\frac{\dot{A}_i(t)}{A_i(t)} = (g-c)H_i(t) + cH_i(t)\frac{A_m(t)}{A_i(t)}$ when assuming that g and c are simply coefficients of H_i. However, here, the matrix of explanatory variables further includes the interaction term's second main term $\boldsymbol{a}$. Otherwise, the interaction term may be significant due to left-out variable bias (Balli & Sorensen, 2013).

3 Data

The sample is a cross-section of 569 regions in 30 countries, with data for the period 1980-2005. A list of the country names and the amount of regions per country covered by the sample is given in the appendix. The units of observation are regions at the most disaggregated administrative or statistical division of countries where data was available, often represented by provinces. Concerning European regions, the statistical classification NUTS-2 is used, since it is commonly viewed as the most appropriate unit for modelling and analysis purposes (e.g Fingleton, 2001). The main data source is the data provided by Gennaioli et al. (2014), who collected an extensive amount of yearly data for measures of regional gross domestic product (GDP), human capital and geography. In some cases their data needed to be aggregated to the higher statistical unit in order to match the information describing the geographic location of regions[3]. For this computation, population data from the Eurostat Regional Database were retrieved (Eurostat, 2015). In other cases, data from Gennaioli et al. (2014) was aggregated at a higher level than the geographical data, but such regions could be merged using a geographic software.

The measure for **total factor productivity** is constructed by assuming constant returns to scale for the regional Cobb-Douglas production function with the capital share set at 1/3 and the labor share set at 2/3. This approach is consistent with Benhabib & Spiegel (2005). For region i in period t

$$lnA_{it} = lnY_{it} - \frac{1}{3}lnK_{it} - \frac{2}{3}lnL_{it}$$

where A_{it} is TFP of region i at time t, Y_{it} is GDP, K_{it} is the physical capital stock and L_{it} is the population respectively. The average annual growth rates of TFP for the period 1980-2005 are then calculated as the differences of the natural logarithm in 1980 and 2005 and dividing by the number of years in the time interval.

Gennaioli et al. (2014) offer data on regional GDP per capita in current purchasing power US$ values. This was obtained by multiplying national GDP in purchasing power parity (PPP) terms by the share of each region in national GDP, since there are no regional price deflators available. They further provide data on regional population density. To obtain the absolute population size from their population density data, the areas of the regions

[3] This was done for the regions of Bulgaria, the Czech Republic, Hungary, Ireland, Romania, and Spain.

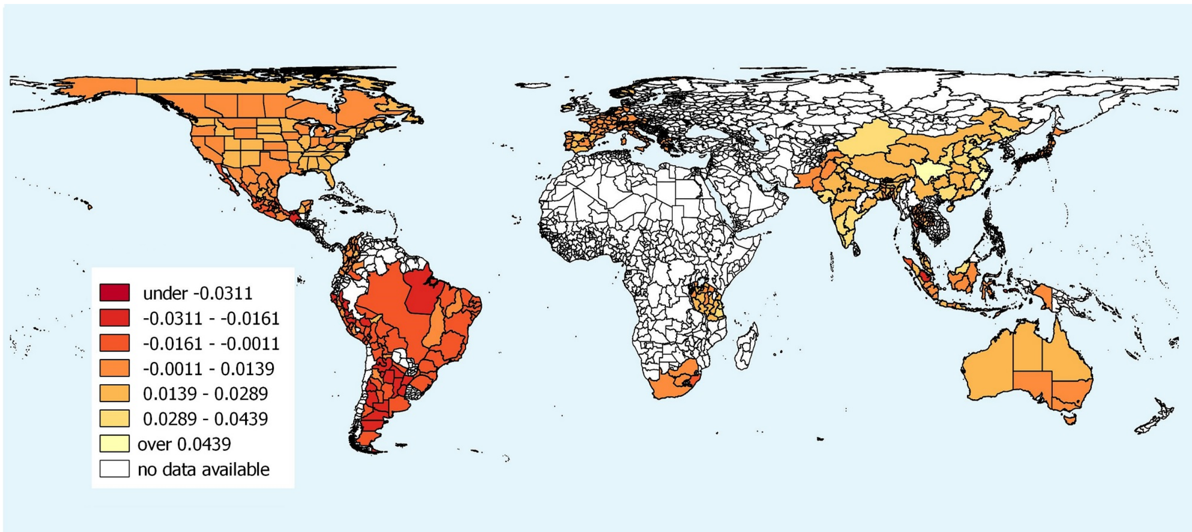
are computed in QGIS, using data on geographic location from the Natural Earth Database (Natural Earth, 2015). These population numbers are further used to obtain total GDP from the GDP per capita data. Regions for which there are no data available for the years 1980 and/or 2005 are still included in the sample if there are observations for some years between 1977 and 1983 and between 2002 and 2008 available. In order to derive estimates for the regional stocks of physical capital, estimates for countries' stocks of physical capital (at current PPPs in US$ values) were retrieved from the Penn World Tables 8.0. (Feenstra et al., 2015) to be multiplied by the share of each region in national GDP.

The measure for regional **human capital stocks** is average years of schooling, also obtained from the data set provided by Gennaioli et al. (2014). Following the methodology by Barro & Lee (2013), they computed average years of schooling as the weighted sum of the years of school required to achieve each educational level. The weights are the fraction of the population aged 15 and older that has completed each level of education. They used UNESCO data on the duration of primary and secondary school in each country and further assumed four years of school for the tertiary level. In conformity with Benhabib & Spiegel (1994, 2005), initial values for human capital should be used in the model estimation, i.e. average years of schooling in the year 1980, in order to minimize problems of endogeneity. Nevertheless, a robustness check will be conducted when taking the average of human capital stocks over the estimation period and including this measure in the regression model instead of initial human capital stocks. Since 1980 and 2005 data on years of schooling were missing for some regions, they had to be extrapolated in these cases.

Basic geographical data on the location of each region given by longitude and latitude were retrieved from Natural Earth database (Natural Earth, 2015). This was used to calculate a centroid for each region in GeoDa, in order to determine the distance between each region and other regions. This measure for distance is needed for the k-nearest as well as for the distance-decay specification of neighborhood.

The sample coverage and the spatial distribution of estimates for the growth rates of TFP are illustrated in Figure 1. Not surprisingly, high growth rates can be observed in some Thai and many Chinese and Indian regions, showing their boosting technological progress over the last decades. Low growth rates are observed in many Peruvian, Argentinian and Mexican regions, as well as in other South- and Central-American regions. In general, it seems that high and low growth rates of TFP tend to cluster together in space, pointing to some spatial autocorrelation of regional TFP growth rates.

Figure 1: *Estimates for average annual TFP growth rates (1980-2005)*



Source: own map created in QGIS

Table 1 summarizes the data on TFP, its growth rate, and average years of schooling by presenting some descriptive statistics. TFP is lowest in Pwani, a region in Tanzania, and highest in the region of Oslo. According to the model proposed by Benhabib & Spiegel (1994), this makes Oslo the technology leader region. With reference to growth rates of TFP, half of the observations show growth rates between 0.3 and 1.6 percent. The lowest value of TFP growth is detected in the region of Loreto and Ucayali in Peru, and the highest in the Thai region Rayong. The distribution of average years of schooling is slightly right skewed, with a mean of 5.7 years of school being higher than the median. The region with the lowest human capital stock is Tibet in China and the region with the highest human capital stock is the canton Geneva in Switzerland. Half the regions in the sample show values between 2.7 and 9.3 average years of schooling.

4 Estimation Results

This section presents empirical results of SDM specifications introduced in section 2.2, as well as results of models without spatial dependencies, in order that both approaches can

Table 1: *Descriptive statistics*

Variable	Min.	Mean	Median	Max.	St.dev.
Ln(TFP) (1980)	3.32	5.52	5.84	7.31	0.83
Average annual growth of TFP (1980-2005)	-4.61	0.91	0.96	5.89	1.36
Average years of schooling (1980)	0.50	5.71	4.94	13.07	3.49

Source: own calculations

be compared. First, both types of models are estimated for regions *between* countries, and second for regions *within* countries. In the latter case, the regressions are carried out using country-specific intercepts. This can reduce omitted variable problems by controlling for the large cross country heterogeneity in national institutions, quality of the education, labor productivity and other unobserved variables at the country level (Gennaioli et al., 2014). In a spatial model setting, spatial spillovers can still cross country borders when using country-specific intercepts, but the regions converge to a country-specific steady state.

The SDM specifications are estimated with maximum likelihood estimation methods (MLE) using the spatial econometric toolbox developed by LeSage (1998). The k-nearest spatial weight matrix is computed for $k = 5$. Results for other values of k are presented later as part of the robustness checks. Further robustness checks are conducted for model specifications containing some additional explanatory variables, for using average human capital stocks instead of initial human capital stocks and for truncating the dependent variable in order to exclude potential outliers.

4.1 Linear regression model for regions between countries

To begin, column (I) in table 2 presents the regression results of a model without a spatial lag in the dependent variable. This implies that the parameter ρ in equation 2 is set to zero and that the model can be estimated by ordinary least squares (OLS). The results refer to the explanatory variables years of schooling, technology gap and the interaction term as defined above. They show that all coefficient estimates are highly significant and have the expected signs. However, interpreting the effects of years of schooling and the technology gap on TFP growth requires to take the non-linearity of the interaction term into consideration. Consistent with Balli & Sorensen (2013), this is done by calculating the marginal effects of the main terms. Referring to human capital, for example, the matrix of partial derivatives of

TFP growth with respect to average years of schooling is given by

$$\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{h}'} = \boldsymbol{I}_N \beta_1 + \text{diag}(\boldsymbol{a})\beta_3 \tag{3}$$

where diag($\boldsymbol{a}$) spans the elements of vector $\boldsymbol{a}$ on the main diagonal of a diagonal matrix. Hence, the interpretation of β_1 is the partial derivative of TFP growth with respect to years of schooling when the measure for the technology gap is equal to zero. Then, an increase of average years of schooling by one year would increase the TFP growth rate by 0.11 percentage points. However, this scenario is impossible by construction since $a_i \geq 1$ for all $i = 1, ..., N$. In general, it is not very sensible to analyze cases where one of the main terms is set to zero when this is not representative of the distribution of this main term. Therefore, the interpretation of partial derivatives is given for different levels in the distribution of years of schooling and of the technology gap. This shows that an increase of average schooling by one year for a region at the first quartile, at the median, and at the third quartile in the distribution of technology gaps, translates to an increase of TFP growth rates by 0.33, 0.48, and 1.34 percentage points respectively. According to the model by Benhabib & Spiegel (1994) this implies that regions with lower TFP levels, i.e. with a larger gap to the technology leader, benefit more from increasing human capital levels than regions with more advanced technology, because in addition to enhancing domestic innovation, human capital facilitates technology adoption from abroad. Similarly, the speed of technological catch-up increases with higher values of human capital.

Table 2: *Estimation results*

Specification	(I)	(II)	(III)	(IV)	(V)	(VI)
$\boldsymbol{h}$	0.0011***	0.0009*	0.0001	0.0002	−0.0006	−0.0001
	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
$\boldsymbol{a}$	0.0006***	0.0004***	0.0005***	0.0005***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\boldsymbol{h} \circ \boldsymbol{a}$	0.0002***	0.0002***	0.0003***	0.0002***	0.0003***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{Wh}$			0.0003	−0.0006	0.0000	0.0000
			(0.0004)	(0.0004)	(0.0005)	(0.0005)
$\boldsymbol{Wa}$			−0.0004**	−0.0008***	−0.0004***	−0.0008***
			(0.0001)	(0.0002)	(0.0002)	(0.0002)
$\boldsymbol{Wh} \circ \boldsymbol{a}$			−0.0002***	0.0001	−0.0001**	0.0000
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
ρ			0.7080***	0.1290**	0.6090***	0.0900
			(0.0311)	(0.0586)	(0.0387)	(0.0601)
Country FE	NO	YES	NO	YES	NO	YES
Add. controls	NO	NO	NO	NO	YES	YES
R^2	0.260	0.720	0.265	0.736	0.490	0.748
adj. R^2	0.256	0.704	0.257	0.720	0.473	0.727
log L	1725	2005	2097	2218	2122	2229
N	569	569	569	569	569	569

Notes Additional controls: lnoilgas, lnpopden, capcity, invcoast, malaria, OECD. W is a k-nearest neighbour matrix with $k = 5$. Constant not reported in table. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.2 SDM for regions between countries

Column (III) in table 2 shows the results of carrying out an SDM estimation. The results demonstrate relatively strong spatial autocorrelation of the dependent variable TFP growth rates. This is reflected by the parameter estimate for ρ, which is highly significant.

Concerning the estimated slope parameters of Spatial Durbin Models, they cannot be interpreted as compared to classical linear models (LeSage & Pace, 2009). As a result of the spatial lag in the dependent and independent variables, possible spillovers and feedback loops need to be considered. For instance, a change in human capital stock in a region i may not only affect its own TFP growth rate, but also the TFP growth rates and human capital stocks in other regions, including region j. A change in region j's TFP growth rate and human capital stock, however, again has an impact on the TFP growth rate in region i and so on. LeSage & Pace (2009) provide specific impact measures which are required to interpret the estimation coefficients of spatial models with endogenous spillover effects. Building upon the partial derivative, they summarize the direct and indirect impacts to scalar measures and draw statistical inferences for them.

When including an interaction term in the model, the impact measures by LeSage & Pace (2009) need to be extended. Following computations by Piribauer & Wanzenboeck (2015), the impacts of human capital on TFP growth are then given by the partial derivatives

$$\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{h}'} = (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}(\boldsymbol{I}_N \beta_1 + \mathrm{diag}(\boldsymbol{a})\beta_3 + \boldsymbol{W}\theta_1 + \boldsymbol{W}\mathrm{diag}(\boldsymbol{a})\theta_3) \tag{4}$$

where $\mathrm{diag}(\boldsymbol{a})\beta_3$ and $\boldsymbol{W}\mathrm{diag}(\boldsymbol{a})\theta_3$ are the terms added due to the interaction.[4] In order to obtain scalar measures for direct impacts, indirect impacts and total impacts, the partial derivatives matrix is summarized as proposed by LeSage & Pace (2009). Taking the average over the main diagonal elements gives the direct impact. Similarly, the indirect impact is calculated by taking the average over the off-diagonal entries of the matrix. The total impact is the sum of the direct and indirect impact. The results of these impact measures for both main terms, average years of schooling and the technology gap, are presented in the first three columns of table 3. Along with the mean impact estimates, table 3 reports a confidence interval obtained by 1000 sampled parameter estimates. The impact of a variable is significantly different from zero if the upper and the lower bound of the interval both show the same sign. The results demonstrate that increasing regions i's years of schooling by one year, on average leads to an increase of regions i's TFP growth rate by 0.29 percentage points, taking all feedback loops into account. Surprisingly, the impact of an increase in human capital on all other regions is negative. The positive estimate for the direct impact of the technology gap implies that technologically less developed regions on average experience higher TFP growth

[4] Obviously, the impacts of the technology gap on TFP growth are given by $\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{a}'} = (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}(\boldsymbol{I}_N \beta_2 + \mathrm{diag}(\boldsymbol{h})\beta_3 + \boldsymbol{W}\theta_2 + \boldsymbol{W}\mathrm{diag}(\boldsymbol{h})\theta_3)$.

rates. The negative spillover effect of the technology gap indicates positive spillovers of total factor productivity, since smaller gaps are attributed to higher TFP levels.

Note that by computing impacts in the preceding way, the interpretation of the impact of a main term is conditional on the average level of the other main term. In other words, a one year increase of years of schooling leads to an increase of 0.29 percentage points of the TFP growth rate, *given that the technological distance to the technology leader is average compared to the other regions*. Analogous to the analysis of the linear model regression, further impacts are calculated when the other main term is evaluated at the first and the third quartile of its distribution. These results are reported in the second and third column block of table 3. All impacts are significant and have the same signs as when the other main term is averaged. In line with the results of the linear regression model, the direct impact of human capital on TFP growth is higher in regions with less technology. Likewise, technological catch-up is supported by human capital since the rate of technological catch-up is larger in regions with more years of schooling. Nevertheless, the magnitudes of the impacts are substantially lower than in the linear regression model. The linear model seems to assign parts of the effect caused by spatial autocorrelation in the dependent variable to the impacts of the explanatory variables.

Table 3: *Impact estimates for SDM (Spec. (III))*

	Average (1)			**1st Quartile (2)**			**3rd Quartile (3)**		
Variables	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99
				Average direct impact					
Human capital $\boldsymbol{h}$	0.0017	0.0029	0.0039	0.0001	0.0010	0.0018	0.0027	0.0040	0.0053
Technology gap $\boldsymbol{a}$	0.0019	0.0024	0.0030	0.0011	0.0015	0.0018	0.0026	0.0036	0.0046
				Average indirect impact					
Human capital $\boldsymbol{h}$	−0.0035	−0.0024	−0.0013	−0.0016	−0.0007	0.0001	−0.0049	−0.0034	−0.0020
Technology gap $\boldsymbol{a}$	−0.0028	−0.0022	−0.0016	−0.0016	−0.0013	−0.0010	−0.0043	−0.0032	−0.0022
				Average total impact					
Human capital $\boldsymbol{h}$	0.0002	0.0004	0.0008	0.0001	0.0003	0.0005	0.0001	0.0006	0.0010
Technology gap $\boldsymbol{a}$	0.0001	0.0003	0.0004	0.0001	0.0002	0.0003	0.0001	0.0004	0.0007

4.3 Linear regression model for regions within countries

Column (II) in table 2 displays the estimation results of the linear model when concentrating on regional differences within countries. Therefore, country dummies are included to control for country-specific characteristics. In general, the results for including country-specific effects are considered more reliable since they control for all unobserved variables at the country level, for example national institutions and education systems. In light of the rather strong country heterogeneity in the underlying sample, this should be particularly relevant. The results show that the adjusted coefficient of determination R^2 has increased from 0.26 to 0.70 compared to the model estimation without country-specific effects, implying that these effects explain a large share of the variability in TFP growth rates. Even though the catch-up effect of regions with less technology experiencing higher TFP growth rates is slightly smaller in this specification, it remains robust at the one percent level. In contrast, the main term human capital is only significant at the ten percent level but, most importantly, the coefficient of the interaction term remains the same in its magnitude and its significance also when considering regional differences within countries.

4.4 SDM for regions within countries

The results of a SDM estimation for regions within countries are reported in column (IV) in table 2. The fact that the parameter estimate for ρ decreased from 0.71 to 0.13 shows that by controlling for country-specific effects, to a large extent one also controls for the positive spatial autocorrelation of TFP growth rates. This result is not surprising, given that country effects themselves constitute a spatial specification in the wider sense (Crespo Cuaresma et al., 2014).

The log-likelihood is 2218. For completeness, it is worth noting that this result has been compared to the log-likelihoods of model specifications where the restrictions a) $\theta_1 = 0$, $\theta_2 = 0$, $\theta_3 = 0$ or b) $\theta_1 + \rho\beta_1 = 0$,$\theta_2 + \rho\beta_2 = 0$, $\theta_3 + \rho\beta_3 = 0$ are imposed on the parameters. These restrictions make the Spatial Durbin Model collapse into a) a Spatial Autoregressive Model (SAR) or b) a Spatial Error Model (SEM). I calculate twice the difference between the log-likelihoods of the SDM and the SAR model (34.2) and between the log-likelihoods of the SDM and the SEM model (27.0) and find that in both of the cases the 99% critical value of a $\chi^2(3)$ distribution (11.34) is exceeded. It follows that the likelihood-ratio test provides no evidence that a SAR or SEM specification is favoured over the SDM specification. For interpreting the impacts of the explanatory variables, the same method as was introduced in subsection 4.2 should be employed.

Table 4 presents the impact measures corresponding to the preceding SDM estimation results. Though slightly smaller than in the estimation for regions between countries, the direct impact of human capital is still significant and increases with larger TFP gaps. This underlines the importance of the interaction effect. As far as the catch-up coefficient is concerned, the gap between a region and the overall technology leader is closed by 0.24 percent each year when human capital is average. For regions where human capital stocks are above average, for example at the 75$^{\text{th}}$ percentile of the distribution, the catch-up speed is considerably faster with 0.36 percent. In addition to the direct impact, the indirect impact of the catch-up coefficient also remains significant. As before, this is interpreted as positive spillovers of technology levels. In spite of the fact that the present results refer to a setting of regional differences within countries, the positive technology spillovers can still cross country borders. With regard to human capital, the negative indirect impact found in the specification without country dummies is not significant anymore.

Table 4: Impact estimates for SDM, with country fixed effects (Spec. (IV))

	Average (1)			**1st Quartile (2)**			**3rd Quartile (3)**		
Variables	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99
				Average direct impact					
Human capital $\boldsymbol{h}$	0.0010	0.0021	0.0033	0.0000	0.0009	0.0019	0.0014	0.0028	0.0041
Technology gap $\boldsymbol{a}$	0.0014	0.0020	0.0026	0.0010	0.0013	0.0017	0.0018	0.0027	0.0038
				Average indirect impact					
Human capital $\boldsymbol{h}$	−0.0021	−0.0011	0.0000	−0.0015	−0.0007	0.0001	−0.0027	−0.0013	0.0001
Technology gap $\boldsymbol{a}$	−0.0019	−0.0013	−0.0006	−0.0014	−0.0011	−0.0007	−0.0026	−0.0015	−0.0005
				Average total impact					
Human capital $\boldsymbol{h}$	0.0004	0.0010	0.0017	−0.0003	0.0002	0.0008	0.0006	0.0015	0.0026
Technology gap $\boldsymbol{a}$	0.0003	0.0007	0.0011	0.0001	0.0003	0.0005	0.0005	0.0012	0.0020

4.5 Robustness checks

In this section, robustness checks are performed to find out whether the results hold in different settings. The first robustness check repeats the estimation adding further explanatory variables to the regression model. A variable which is frequently considered in regional growth analysis is an indicator for whether the capital city of the country lies in the particular region. Further explanatory variables available in the data set by Gennaioli et al. (2014) are per capita cumulative oil and gas production, population density, a region's inverse distance to coast and an index for malaria ecology. I also add a dummy for a country's OECD membership. The coefficient estimates when adding these variables are reported in column (V) and (VI) in table 2. The estimates of the parameter ρ decrease when adding the further controls, in both of the cases with and without country-specific effects. This indicates that the variables control for some of the spatial autocorrelation of TFP growth rates. Concerning the case including country dummies, the estimate for ρ even becomes insignificant.

The results in table 5 and table 6 point out that the positive direct impacts of human capital and the technology gap are still present when controlling for the additional variables available in the data set by Gennaioli et al. (2014). In spite of the direct impact of human capital not being significantly positive for technologically advanced regions, it shows a significant and positive sign for regions at the technological average and below. Moreover, the positive spillovers of technology levels remain robust. Referring to the control variables, only the OECD dummy has a significant and positive direct impact on TFP growth. However, the effect becomes insignificant when adding country-specific effects. As far as the other variables are concerned, no significant impacts on technological progress are observed.

Table 5: *Impact estimates for SDM, additional controls (Spec. (V))*

	Average (1)			**1st Quartile (2)**			**3rd Quartile (3)**		
Variables	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99
				Average direct impact					
Human capital $\boldsymbol{h}$	0.0013	0.0024	0.0036	−0.0007	0.0004	0.0014	0.0023	0.0037	0.0051
Technology gap $\boldsymbol{a}$	0.0021	0.0026	0.0032	0.0012	0.0015	0.0019	0.0029	0.0039	0.0050
Lnoilgas	−0.1722	−0.0200	0.1199	−0.1722	−0.0200	0.1199	−0.1722	−0.0200	0.1199
Lnpopden	−0.0013	−0.0004	0.0005	−0.0013	−0.0004	0.0005	−0.0013	−0.0004	0.0005
Capcity	−0.0007	0.0041	0.0089	−0.0007	0.0041	0.0089	−0.0007	0.0041	0.0089
Invcoast	−0.0197	0.0034	0.0243	−0.0197	0.0034	0.0243	−0.0197	0.0034	0.0243
Malaria	−0.0009	−0.0003	0.0004	−0.0009	−0.0003	0.0004	−0.0009	−0.0003	0.0004
OECD	0.0051	0.0205	0.0344	0.0051	0.0205	0.0344	0.0051	0.0205	0.0344
				Average indirect impact					
Human capital $\boldsymbol{h}$	−0.0031	−0.0020	−0.0007	−0.0014	−0.0004	0.0007	−0.0044	−0.0029	−0.0015
Technology gap $\boldsymbol{a}$	−0.0027	−0.0021	−0.0014	−0.0016	−0.0013	−0.0009	−0.0042	−0.0031	−0.0019
Lnoilgas	−0.0381	0.1453	0.3703	−0.0381	0.1453	0.3703	−0.0381	0.1453	0.3703
Lnpopden	−0.0004	0.0006	0.0016	−0.0004	0.0006	0.0016	−0.0004	0.0006	0.0016
Capcity	−0.0085	−0.0025	0.0041	−0.0085	−0.0025	0.0041	−0.0085	−0.0025	0.0041
Invcoast	−0.0261	0.0014	0.0273	−0.0261	0.0014	0.0273	−0.0261	0.0014	0.0273
Malaria	−0.0003	0.0004	0.0011	−0.0003	0.0004	0.0011	−0.0003	0.0004	0.0011
OECD	−0.0302	−0.0164	−0.0013	−0.0302	−0.0164	−0.0013	−0.0302	−0.0164	−0.0013
				Average total impact					
Human capital $\boldsymbol{h}$	0.0001	0.0004	0.0008	−0.0003	0.0000	0.0002	0.0003	0.0008	0.0013
Technology gap $\boldsymbol{a}$	0.0003	0.0006	0.0008	0.0002	0.0003	0.0004	0.0005	0.0009	0.0013
Lnoilgas	0.0109	0.1253	0.2487	0.0109	0.1253	0.2487	0.0109	0.1253	0.2487
Lnpopden	−0.0002	0.0002	0.0005	−0.0002	0.0002	0.0005	−0.0002	0.0002	0.0005
Capcity	−0.0037	0.0016	0.0068	−0.0037	0.0016	0.0068	−0.0037	0.0016	0.0068
Invcoast	−0.0116	0.0048	0.0205	−0.0116	0.0048	0.0205	−0.0116	0.0048	0.0205
Malaria	−0.0001	0.0001	0.0003	−0.0001	0.0001	0.0003	−0.0001	0.0001	0.0003
OECD	0.0020	0.0041	0.0062	0.0020	0.0041	0.0062	0.0020	0.0041	0.0062

Table 6: *Impact estimates for SDM, additional controls with country fixed effects (Spec. (VI))*

	Average (1)			**1st Quartile (2)**			**3rd Quartile (3)**		
Variables	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99	Lower 0.01	Mean	Upper 0.99
				Average direct impact					
Human capital $\boldsymbol{h}$	0.0005	0.0018	0.0031	−0.0007	0.0005	0.0017	0.0012	0.0024	0.0038
Technology gap $\boldsymbol{a}$	0.0015	0.0020	0.0025	0.0008	0.0011	0.0014	0.0017	0.0025	0.0033
Lnoilgas	−0.1453	−0.0178	0.1053	−0.1048	−0.0006	0.1052	−0.1033	−0.0010	0.1107
Lnpopden	−0.0008	0.0001	0.0011	−0.0006	0.0001	0.0010	−0.0006	0.0001	0.0009
Capcity	−0.0022	0.0024	0.0069	−0.0022	0.0016	0.0055	−0.0023	0.0017	0.0053
Invcoast	−0.0168	0.0021	0.0215	−0.0109	0.0037	0.0186	−0.0115	0.0038	0.0202
Malaria	−0.0003	0.0003	0.0009	−0.0002	0.0003	0.0008	−0.0002	0.0003	0.0008
OECD	−0.0072	0.0099	0.0277	−0.0067	0.0083	0.0222	−0.0065	0.0082	0.0236
				Average indirect impact					
Human capital $\boldsymbol{h}$	−0.0020	−0.0009	0.0003	−0.0010	0.0000	0.0011	−0.0012	0.0007	0.0024
Technology gap $\boldsymbol{a}$	−0.0021	−0.0015	−0.0008	−0.0012	−0.0007	−0.0002	−0.0017	−0.0003	0.0012
Lnoilgas	−0.1056	0.0834	0.2533	−0.1168	0.1450	0.4520	−0.1532	0.1460	0.4380
Lnpopden	−0.0010	0.0001	0.0012	−0.0009	0.0004	0.0016	−0.0010	0.0003	0.0016
Capcity	−0.0095	−0.0040	0.0016	−0.0150	−0.0048	0.0055	−0.0147	−0.0047	0.0049
Invcoast	−0.0192	0.0063	0.0339	−0.0196	0.0142	0.0531	−0.0213	0.0153	0.0526
Malaria	−0.0007	0.0000	0.0006	−0.0004	0.0003	0.0008	−0.0005	0.0002	0.0009
OECD	−0.0234	−0.0093	0.0046	−0.0182	−0.0067	0.0052	−0.0186	−0.0069	0.0050
				Average total impact					
Human capital $\boldsymbol{h}$	0.0001	0.0009	0.0018	−0.0011	0.0005	0.0021	0.0009	0.0031	0.0052
Technology gap $\boldsymbol{a}$	0.0001	0.0006	0.0010	−0.0001	0.0004	0.0009	0.0007	0.0022	0.0038
Lnoilgas	−0.0678	0.0656	0.1877	−0.1228	0.1444	0.4221	−0.1360	0.1450	0.4304
Lnpopden	−0.0003	0.0002	0.0008	−0.0007	0.0005	0.0017	−0.0008	0.0004	0.0017
Capcity	−0.0074	−0.0015	0.0041	−0.0152	−0.0032	0.0097	−0.0154	−0.0030	0.0090
Invcoast	−0.0065	0.0085	0.0258	−0.0167	0.0179	0.0532	−0.0163	0.0191	0.0558
Malaria	0.0000	0.0003	0.0005	0.0000	0.0005	0.0011	0.0000	0.0005	0.0011
OECD	−0.0063	0.0006	0.0080	−0.0142	0.0015	0.0174	−0.0144	0.0013	0.0165

As another robustness check the role outliers is examined. Following Gennaioli et al. (2014) all observations with TFP growth rates below the 5^{th} and above the 95^{th} percentile are excluded from the sample. The results presented in table 7 confirm the foregone findings since the coefficients corresponding to the variables of interest stay significant and show the expected signs. The parameter estimate for ρ, however, becomes lower and insignificant as soon as country fixed effects are added to the model. The average impacts accounting for the feedback loops caused by the endogenous lag of the dependent variable are also in line with the previous results [5].

Following Benhabib & Spiegel (1994, 2005), the concern should be addressed that initial human capital stocks might not be a good proxy for human capital stocks in the estimation period. Human capital stocks often increase over time, so instead of using initial human capital stocks, the average of human capital stocks over the estimation period 1980-2005 is considered. However, also for this specification, the impact estimates remain robust[6].

Another set of robustness checks is computed for different specifications of the spatial weight matrix $\boldsymbol{W}$. First, the value for the parameter k in the k-nearest specification is considered. Conducting regressions for $k = 4, k = 6, k = 7$, and $k = 20$ indicated that the estimation results do not depend on the assumption of how many regions are considered as first-order neighbors. Despite the decrease of spillover intensity over space, the presence of a spatial lag in the dependent variable leads to global spillovers anyway. Comparing the sum of squared residuals for model estimations employing these different values of k, showed that the sum of squared residuals is minimized for $k = 5$ in the model with country effects. Second, a distance-decay matrix is calculated. Prior to row standardization, an element of a distance-decay matrix is given by $W_{ij} = d_{ij}^{-\delta}$, where d refers to the distance between region i and j and δ is a given decay parameter. Assuming $\delta = 1$ gives an inverse-distance matrix. Defining the spatial weight matrix according to inverse-distances yields estimation results that highly resemble the results obtained by a k-nearest spatial weight matrix when $k = 5$. However, the sum of squared residuals from a model estimation using the k-nearest neighbor specification is lower than with inverse-distances. From all this, it follows that the above presented estimation results are robust to different spatial diffusion patterns, as well as to excluding outliers and

[5] The impact tables for the truncated data are available upon request.

[6] The results are available upon request

to variations in the explanatory variables.

Table 7: Estimation results for obs. between 5th and 95th perc. of TFP growth

Specification	(I)	(II)	(III)	(IV)	(V)	(VI)
$\boldsymbol{h}$	0.0010∗∗∗	0.0007∗∗	0.0002	0.0002	−0.0002	−0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
$\boldsymbol{a}$	0.0004∗∗∗	0.0003∗∗∗	0.0004∗∗∗	0.0004∗∗∗	0.0004∗∗∗	0.0004∗∗∗
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\boldsymbol{h} \circ \boldsymbol{a}$	0.0001∗∗∗	0.0002∗∗∗	0.0002∗∗∗	0.0002∗∗∗	0.0002∗∗∗	0.0002∗∗∗
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{Wh}$			0.0001	−0.0007	−0.0003	−0.0006
			(0.0003)	(0.0003)	(0.0004)	(0.0004)
$\boldsymbol{Wa}$			−0.0003∗∗∗	−0.0008∗∗∗	−0.0004∗∗∗	−0.0007∗∗∗
			(0.0001)	(0.0002)	(0.0001)	(0.0002)
$\boldsymbol{Wh} \circ \boldsymbol{a}$			−0.0001∗∗	0.0002∗∗∗	0.0000	0.0002∗∗
			(0.0000)	(0.0001)	(0.0001)	(0.0001)
ρ			0.6340∗∗∗	0.0770	0.5960∗∗∗	0.0560
			(0.0350)	(0.0636)	(0.0415)	(0.0652)
Country FE	NO	YES	NO	YES	NO	YES
Add. controls	NO	NO	NO	NO	YES	YES
R^2	0.256	0.704	0.262	0.724	0.456	0.739
adj. R^2	0.251	0.685	0.253	0.705	0.436	0.713
log L	1706	1942	2021	2138	2049	2151
N	511	511	511	511	511	511

Notes Additional controls: lnoilgas, lnpopden, capcity, invcoast, malaria, OECD. W is a k-nearest neighbour matrix with $k = 5$. Constant not reported in table. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusion

This paper analyzes the nature of technology diffusion and the impact of human capital on technology growth for 569 sub-national regions in 30 countries, including 15 non-OECD countries. By imposing a spatial econometric structure on the Benhabib & Spiegel (1994) model, it allows for technology spillovers via three channels. First, technological distance to the technology leader can influence the intensity of the spillovers. Second, technology spillovers may depend on the stock of human capital, which determines the speed of technology adoption.

Third, technology spillovers can be affected by geographical distance, supposing that regions have greater access to technology resources of neighbors than of non-neighbors.

The results indicate that technology diffusion in regions takes place over all the above mentioned channels. In particular, they show that human capital and technological catch-up are robust drivers of total factor productivity growth, and that the speed of technological catch-up increases with increasing human capital stocks. Furthermore, positive spatial spillovers of technology levels on TFP growth can be observed. These findings correspond to both cases when considering differences of regions between countries as well when considering differences of regions within countries. Due to the fact that the latter specification controls for all unobserved variables at the country level, the impact estimates for education and the technology gap are slightly lower than without country-specific effects. In general, the findings hold when adding population density, per capita oil and gas production, a region's inverse distance to coast, an index for malaria ecology and dummies for the location of a country's capital city and its OECD membership as further explanatory variables to the baseline model. While the positive direct impact associated with human capital becomes insignificant for technologically advanced regions, it still shows significant and positive effects for regions at the technological average and below. Notably, for non of the additional variables considered, significant impacts on technology growth are observed. This emphasizes the relevance of technology diffusion via the three channels identified, catch-up, human capital and spatial spillovers, also for regions in less developed economies. Furthermore, the results are robust to using average instead of initial human capital stocks, to variations in the spatial diffusion patterns, as well to excluding potential outliers from the sample data.

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6 Annex

Table 8: *Countries and the amount of regions per country in the sample*

Country	Number of regions
Argentina	24
Australia	8
Austria	9
Bangladesh	7
Bolivia	9
Brazil	20
Canada	11
Switzerland	23
China	27
Colombia	24
Germany	9
Denmark	1
Spain	17
France	20
Greece	7
Indonesia	26
India	27
Ireland	1
Italy	19
Japan	46
Mexico	32
Malaysia	10
Norway	19
Pakistan	4
Peru	23
Portugal	5
Thailand	66
United Republic of Tanzania	20
United States of America	51
South Africa	4