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Technological Diffusion and Productivity Convergence across European Regions: a Spatial Approach over the Period 2000-2015*

Fabio Manca (OECD), Giuseppe Piroli (European Commission)

Abstract: What are the drivers of growth and convergence in productivity at regional level? Differences in the stock of human capital across regions are hypothesized to be the major cause of differences in the speed by which following regions converge and catch-up with the most advanced ones. In addition, we test the role played by R&D expenditures and institutions exploiting a database covering European regions from 1995 to 2015, which includes regional total factor productivity (TFP) computed by the conventional residual approach. We find robust empirical evidence for these hypotheses in terms of both model specifications and sectoral disaggregation.

Keywords: Regional Studies, European Regions, Catching-up, Total Factor Productivity, Human Capital, R&D, Institutions, Spatial Models, Panel Data Models

JEL: P48, D24, J24, E02, C31, C33

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1. Introduction

Different regions grow in productivity at different paces reflecting geographical and local peculiarities. Understanding the factors behind these processes is a relevant issue for both policy makers and researchers. Literature has already studied this topic for a long time identifying the endowment in terms of technological capacity, human capital and R&D capacity as key drivers promoting the productivity's growth in the modern economy. At the same time, following a diffusion process, a region can also benefit from the technological development of the more advanced regions imitating their technology. The idea in of technological catching up across countries was formalised by Richard Nelson and Edmund Phelps in 1966. The original intuition proposed by Gerschenkron (1962) is at the same time appealing, powerful and simple. Countries lagging behind the technological frontier may reduce their gap by imitating technologies discovered in leader countries. Barro and Sala-i-Martin (1997) show that this happens since the costs of imitation in the follower country are usually lower than those of innovation at the frontier are. Hence, the wider the gap and the more the scope for adopting new technologies and therefore the higher, ultimately, the technology growth rates of the lagging country. Crucially, however, the catch-up process is not direct and immediate. Simply lagging behind the leader is not a sufficient condition in order to ensure high growth and catch-up, while regional endowment and capacity play a crucial role.

In fact, Nelson and Phelps (1966), and later Abramovitz (1986) rearranged the catching up hypothesis of Gerschenkron (1962) suggesting how the rate at which the technological gap is closed should be linked to the followers' ability to receive technology flows from the frontier, that is, in their particular case, a function of each country's human capital stock. Later, Benhabib and Spiegel (1994, 2005) empirically tested Nelson and Phelps' (1966) hypothesis showing how differences in human capital stocks may help explaining the observed differences in the speed of technology catch-up across countries.

In this work, we focus on the European regions with the aim of testing the Benhabib and Spiegel (2005) TFP catch-up framework on 265 NUTS 2 European regions for which we build a complete cross-regional database for the period 1995-2015. Following the original model, differences in the stock of human capital across regions (proxied by the average years of schooling in each examined region) are hypothesized to be the cause of differences in the speed by which follower regions converge and catch-up with more developed European regions representing the technology frontier. We find robust empirical evidence for this hypothesis.

Empirical and theoretical literature, however, stress the importance of investments in R&D as one of the channels through which countries (and regions) may increase their productivity levels and economic growth. Coe and Helpman (2008) and Bayoumi et al. (1999) for example, analyse the role played by R&D and human capital contribution to cross country economic growth differentials, while Audretsch and Feldman (1996) study the "geography" of R&D spillovers.

Burda and Severgnini (2017), in a study on the convergence of TFP across German states (Länder), find a significant role of the technological frontier and distance to the frontier. They also confirm that the absorptive capacity channel (R&D spending) is operative in the East German context, helping lagging states to catch up faster. We are going to test expect to find robust empirical evidence for this hypothesis for European regions in our empirical analysis.

The likely presence of spatially correlated spillovers across European regions is of crucial importance for our study. This is to say that the effects of human capital, R&D and the distance from the technological frontier (intended as the difference of each region's technical capabilities w.r.t. the most performing region, the technology leader) may be correlated across space. Human capital, for example, may agglomerate on specific regions (likely the most productive ones) showing a negative spatial correlation w.r.t. neighbouring regions. However, if human capital accumulation is the engine of the TFP catch-up process, then the accumulation in certain geographical areas of large quantities of human capital will shape also the convergence process dramatically. Similarly, R&D expenditures in one region may spatially spill over to neighbouring ones making the creation of innovation (or its absorption) relatively cheaper.

In addition, we test the hypothesis that differences in regional the quality of the regional institutions determinate different speeds in TFP growth. According to Rodríguez-Pose and Ganau (2019), the main issues harming European regions' labour productivity growth are that regions are not making the most of their human capital and innovation potential. Furthermore, institutions are shown to have a strong impact on a region's innovation potential and thus its productivity growth.

We are going to examine a TFP growth model and its determinants covering 265 European regions for the period between 2000 and 2015 adopting a number of spatial econometric models in order to test and control for unobserved spatial heterogeneity.

Our results strongly confirm the presence of spatial dependence in productivity growth and levels across European regions. The proposed econometric models are however able to tackle the spatial dependence and, at the same time, to tell us about the relative importance of human capital and R&D spatial spillovers in the process of productivity convergence. The empirical estimates of the spatially augmented Benhabib and Spiegel's (2005) catch-up model predicts convergence for the European regions. This is mainly driven by higher human capital levels. The effect of human capital acts as engine for innovation as well as an enhancing factor to absorb technologies developed at the technical frontier. At the same time, however, human capital is shown to flow and accumulate in more productive regions, which ignite a virtuous circle leading to faster convergence towards the frontier's productivity level.
In addition, we show the importance of another factor needed to activate the virtuous process: the quality of local institutions. Good regional institutions allow exploiting the economic capacities in broad sense creating the supportive environment for the technological and socio-economic development.

2.1 Human capital, technological diffusion and catching up

We study the role played by human capital and R&D expenditures on the TFP catching up process by means of a logistic model of technology diffusion. The specification used in this present contribution is based on models of economic growth and catch-up that are widely used in the literature on a leader-follower context of economic development (e.g., see Barro and Sala-i-Martin 1995; 1997; Howitt 2000). In this framework, productivity growth is generated through own innovations, knowledge spillovers and technology adoption (catching-up).

In terms of empirical specification, we rely on the widely cited contribution provided by Benhabib and Spiegel (2005) for which the growth rate of productivity, resulting from the technology spillovers, will be a function of the distance of each region from the technology frontier and of the level of human capital.

The basic idea is that technology transfers take place across regions, within the same country or across countries, but that they need some external factors (human capital) in order to be effective. Human capital acts as an enhancing factor for technology flows for which those regions which are endowed with higher levels of human capital will also be those absorbing technology faster (ultimately growing faster).

Empirically, our starting point is the following specification:

$$T\dot{F}P_{r,t} = b_0 + b_1 lnH_{r,t-1} - b_2 \left[lnH_{r,t-1} \times \left(\frac{TFP_{r,t-1}}{TFP^*_{r,t-1}} \right) \right] + e_{r,t} \qquad (1)$$

, where the subscripts *r* stand for "region" and *t* for "time".[1]

The proposed specification relies on the logistic diffusion function proposed by Benhabib and Spiegel (2005). Human capital enters in the two elements of the specification both directly with the coefficient b_1 and through its interaction with the technology gap (coefficient b_2). In the first part, human capital is assumed to increase productivity growth of regions *per se* by fostering innovative activities as in Romer (1990) endogenous growth model. The higher the human capital level and the higher will be the productivity of a region due to its innovative effort.

However, regions also grow by means of technology transfers from the technology frontier. In the second part of the equation, human capital is interacted with the TFP gap in order to capture the absorptive effect that human capital is expected to play on these technology transfers. Two effects are playing here. In principle, the larger the TFP gap and the higher the TFP growth just because "more" technology is out there to be absorbed from the technology frontier. However, in order to be able to absorb this technology, the recipient region needs the appropriate level of human capital. The

[1] In order to simplify the notation, the sectoral dimension i is not reported.

interaction term $b_2\left[lnH_{r,t-1}\times\left(\frac{TFP_{r,t-1}}{TFP^*_{r,t-1}}\right)\right]$ proxies the imitation capacity of region r, which depend on its ability of absorbing[2] the technology coming from the leader region r^*.[3]
We argue that a crucial factor affecting the growth in the productivity is the regional attitude to perform activity in R&D. R&D expenditure, therefore, enters the specification as an additional covariate adding a key feature of the region.

The model also includes an *industrial specialization index* as control variable. In fact, the speed of technology catch-up across regions and underlying dynamics of technology transfers may be dependent on the average specialization of a region. In this light, we built the Krugman Specialisation Index ($KSI_{r,t}$) comparing the industrial structure of the region with the rest of the EU.[4] The index takes the value zero if the region has an industrial structure identical to the reference region, indicating that the region is not specialized, and takes a maximum value of 2 if it has no sectors in common with the rest of the EU, reflecting strong sectoral specialization, according to the following formula for six sectors *i*:

$$KSI_{r,t}=\sum_{r,t}^{i}ABS\left[\frac{X_{r,i}}{X_r}-\frac{X_i-X_{r,i}}{X-X_r}\right] \qquad (2)$$

Hence, the basic empirical specification in eq. (1) will be extended in the following way:

$$T\dot{F}P_{r,t}=b_0+b_1lnH_{r,t-1}-b_2\left[lnH_{r,t-1}\times\left(\frac{TFP_{r,t-1}}{TFP^*_{r,t-1}}\right)\right]+b_3KSI_{r,t-1}+\ b_4RD_{r,t-1}+e_{r,t} \qquad (3)$$

In this specification, we assume that R&D expenditure directly affects the capacity to increase the productivity.

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2 The *absorptive capacity* is the ability to identify, assimilate, and exploit knowledge from the environment (Cohen and Levinthal, 1989). In our model, the absorptive capacity is represented by the human capital.

3 Due to the choice of using a logistic diffusion function for the TFP catch up analysis, we expect a negative sign for the coefficient b_2 meaning that higher levels of human capital interacted with the TFP gap lead to faster TFP growth. For an extensive discussion on the different functional forms, which can be used in this context, see Benhabib and Spiegel (2005).

4 Usually this index is calculated using gross value added or GDP, but we prefer to use employment due to the fact that, having only data for six sectors, it shows higher variability then the index calculated by output, although being highly correlated.

Finally, we test the hypothesis that the quality of institutions plays a critical role enabling well-administrated regions to faster benefit from their potential and progress.

2.2 The spatial approach

The equations from (1) to (3) above summarize the main empirical hypothesis we make on the process of TFP convergence. Eq. (1) and (2) differ by the number of explanatory variables which are assumed to play an role in the process of catch-up, while eq. (3) makes the assumption that R&D expenditures have a role on productivity growth when combined with sufficiently high levels of human capital. As we mentioned in the introduction, our aim is to test for the presence of spatial dependence and, in order to control for it, we make use of seven spatial econometrics models, namely: (i) spatial autoregressive model (SAR), (ii) spatial error model (SEM), (iii) spatial autoregressive combined model (SAC), (iv) spatial lag of x model (SLX), (v) spatial Durbin model (SDM), (vi) spatial Durbin error model (SDEM) and (vii) general nesting spatial model (GNS). Their econometric representation differs in the way we treat the residual term and on the assumptions we make on the spatial dependence across observations.

The spatial lag model assumes that the dependent variable (in our case the growth of productivity) can be explained by a set of explanatory variables and, crucially, by a linear combination of neighbouring values of the dependent variable (that is, in our case the productivity growth of neighbouring regions). The geographical dimension is captured, in our empirical analysis (but in general in the literature), by a matrix of the squared inverse distances across regions.

The spatial error model assumes that the error term exhibit spatial dependence and that this spatial dependence is weighted by the weight matrix of distances as before. The SAC model combines the assumptions of the previous two model, while the spatial lag of x model assumes that the TFP growth is affected by a linear combination of neighbouring values of the explicative variables. The Durbin spatial augments the SLX model by the spatial lags of the dependent variable, while the SDEM adds the spatial lags of the error term. Especially with this last model, we will be able to check the impact of the explicative factors on neighbouring regions and on their productivity growth testing whether spatial spillovers from human capital, R&D expenditure and institutions are taking place across regions. At the same time, the spatial autoregressive model provides the opportunity of taking into account the basic spatial dimension in parsimonious models, which is useful in case of several regressors. For this reason, the

SAC model will be used to test the role of institutions and measure the direct and indirect effects. The general nesting model is the broadest because it incorporates all the spatial effects, but, at the same time, it is very demanding and complex.

4. The data

Data of regional output, capital stock and labour came from the regional database built by Cambridge Econometrics[5]. The time series of regional capital stocks are provided for the period up to 2008[6] and therefore extended by using data on regional gross fixed capital formation from Eurostat and national capital stocks from EU-KLEMS database.[7]

Regarding regional R&D expenditure, we consider relative indicators in order to avoid biases due to scale effects. This is also in line with the recent suggestions in empirical research in response to the critique of Jones (1995) that the absolute scale of R&D resources show little correlation with technological advance. Specifically, we will consider Intramural R&D expenditure (GERD) by NUTS 2 regions as a share of regional GDP extracted from the EUROSTAT database, which captures all spending on R&D carried out within each region in each year

Human capital is calculated computing the number of the schooling years based on the level of formal education according to the International Standard Classification of Education (ISCED) system. EUROSTAT provides data for three different levels of achieved education: i) pre-primary, primary and lower secondary (ISCED 0–2); ii) upper secondary and post-secondary non-tertiary (ISCED 3–4) and iii) first and second-stage of tertiary (ISCED 5–6).

For the years 2010 and 2013, the University of Gothenburg[8] provides the European Quality of Government Index (EQI), built on three main pillars: Quality of government, Corruption and Rule of low. These three indicators are the result of a number of components, where some sub-measures are subjective or based on the perception: the bureaucratic quality (government effectiveness, voice and accountability), the lack/control of corruption and the strength of the rule of law.[9] The database is based on

[5] The authors are grateful to Ben Gardiner (director at Cambridge Econometrics).
[6] See Gardiner et al, 2011.
[7] Main missing information, i.e. national capital stock for Belgium and Portugal, was filled using official national statistics.
[8] The Quality of Government (QoG) Institute: https://qog.pol.gu.se/data.
[9] For further details, see Nicholas Charron, Lewis Dijkstra & Victor Lapuente (2014).

surveys answered by 34 000 respondents (citizens) in 2010 and by 85000 respondents in 2013.

Table 1 presents descriptive statistics from 1995 to 2015, highlighting, on average, the low growth in productivity, while Table 2 remarks a relevant positive correlation between the quality of institutions and the interaction term of our specification (Human Capital x Techn. Gap).

Table 1 – Descriptive Statistics – Total Economy from 1995 to 2015 – NUTS 2 level

	Mean	Std. Dev.	Min	Max
TFP growth	.0068589	.0396059	-.2178019	.3446364
Human Capital	10.0744	.7589893	6.928038	12.75249
Human Capital x Techn. gap	1.02258	.3985594	.1205947	2.508895
KSI	.2642244	.1454297	.030216	1.162434
R&D expenditure	1.363676	1.178201	.0534545	12.19
EQI	59.74701	19.88629	0	100
Corruption	59.88088	20.17056	0	100
Rule of law	61.80846	18.8729	0	100
Quality of government	60.97584	18.81035	0	100

Table 2 – Correlations – Total Regional Economies from 1995 to 2015

	TFP growth	Human Capital	HC x Tech. gap	KSI	R&D	EQI	Corruption	Rule of law	Quality of government
TFP growth	1								
Human Capital	0.1667	1							
HC x gap	-0.0999	0.3601	1						
KSI	-0.1346	-0.1501	-0.5057	1					
R&D expenditure	0.0622	0.3453	0.5153	-0.3068	1				
EQI	0.0813	0.2832	0.705	-0.5086	0.4407	1			
Corruption	0.045	0.287	0.7149	-0.4721	0.4415	0.9643	1		
Rule of law	0.0928	0.2931	0.6775	-0.5031	0.4293	0.9745	0.9186	1	
Quality of government	0.0906	0.2568	0.6693	-0.5117	0.4187	0.9691	0.896	0.9164	1

4.1 The Total Factor Productivity

TFP is that part of economic growth, which does not simply depend on the increase of factor inputs, but results from a more efficient employment of these factors due to technological, organisational, or other progress. Total factor productivity for the NUTS 2 regions in Europe is computed using standard growth accounting methodology over the period 1995-2015.

Our model for TFP follows conventional residual approach:

$$TFP_{r,t} = exp\,\{ln(Y_{r,t}\,) - \alpha_{r,t} \cdot ln(L_{r,t}\,) - (1 - \alpha_{r,t}) \cdot ln(K_{r,t}\,)\} \qquad (4)$$

, where $Y_{r,t}$ is real output (Gross value added)[10] in region r at time t, $K_{r,t}$ is the (physical) capital stock and L_r the total number of workers (labour) at the regional level. Growth of $Y_{r,t}$ is higher than what would result only from higher factor input following the Cobb-Douglas production function[11]. Consistently with the Behnabib and Spiegel (2005) approach, the coefficients $\alpha_{r,t}$ and $(1 - \alpha_{r,t})$ of the production factors (labour and capital), are assumed to be 2/3 and 1/3, respectively[12]. In addition, the labour input is adjusted by working hours, as suggested by the literature, in order to better capture its effective contribution and evolution in a comparable manner between the regions[13].

The map in Figure 1 outlines major differences in regional TFP performances in 2015 clustering regions in eleven classes, where a number of peripheral regions, especially in Eastern Europe, are still lagging behind significantly.

The regions with the higher performance in TFP are Inner London West (29.15),[14] Southern and Eastern Ireland (13.70), Stockholm (13.34), Inner London East (13.33), Luxembourg (12.51) and Île-de-France (11.86), while Severen Tsentralen (2.10), in Bulgaria, Nord-Vest (2.07) and Sud-Vest Olteniaex (1.99), in Romania, present the lowest levels. There is also wide variation within countries as highlighted by the Figure 2[15], where the blue dots represent the regions and the red dots are the country averages.

[10] Gross value added (GVA) is provided by Cambridge Econometrics at constant basic prices in 2000 Euros converting the original current-price (Euro) GVA series from Eurostat's regional accounts into constant prices for each sector by using country-level sectoral price deflators for the year 2000 from the European Commission's AMECO (annual macro-economic) database.

[11] Higher factor input would increase output by $\alpha_{r,t} \cdot d\, ln(L_{r,t}\,) + (1 - \alpha_{r,t}) \cdot d\, \ln(\mathrm{K}_{r,t}\,)$.

[12] For this choice, see also Gollin, Parente, and Rogerson (2002).

[13] See, for example, OECD (2019).

[14] However, given its very peculiar characteristics, Inner London West is considered an outlier.

[15] Data for Croatia are not available. The region of Inner London – West (UKI3) is not included in the chart as it is considered an outlier. FR and PT outermost regions are also excluded.

Figure 1 – TFP in 2015: core and peripheral regions

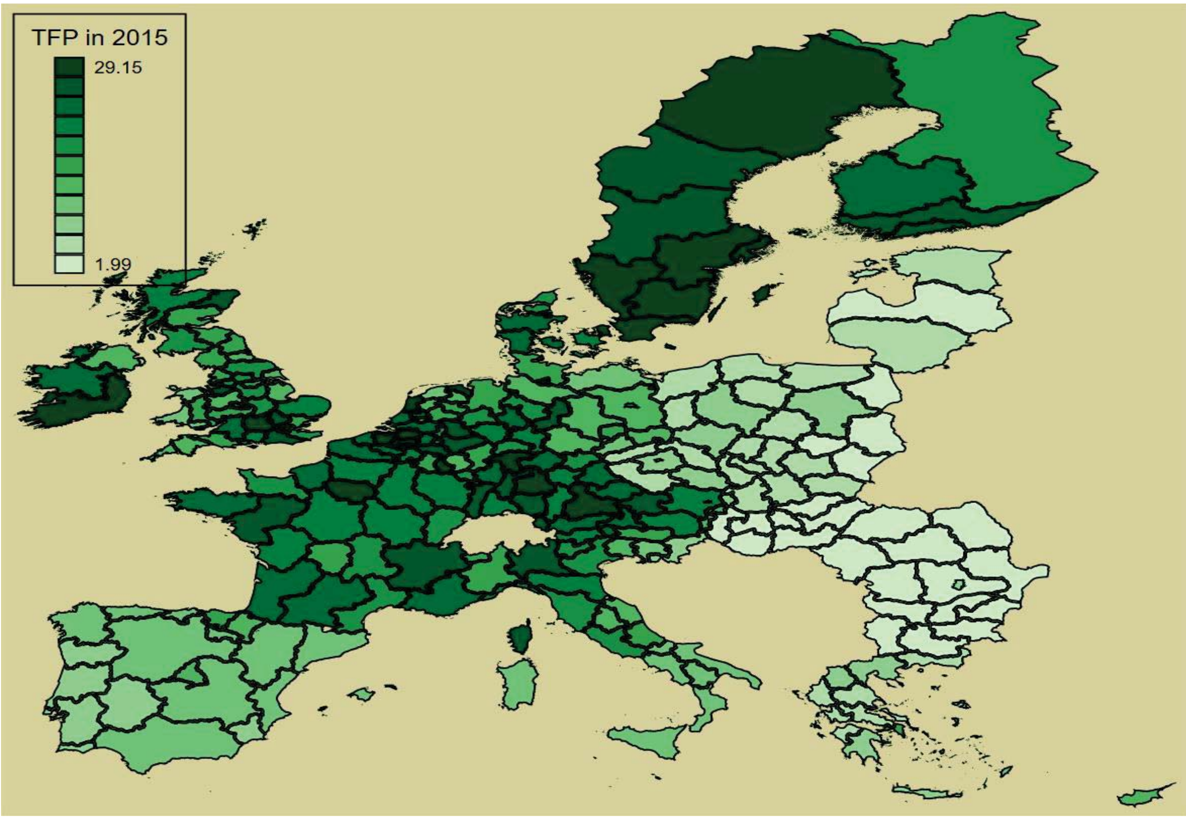
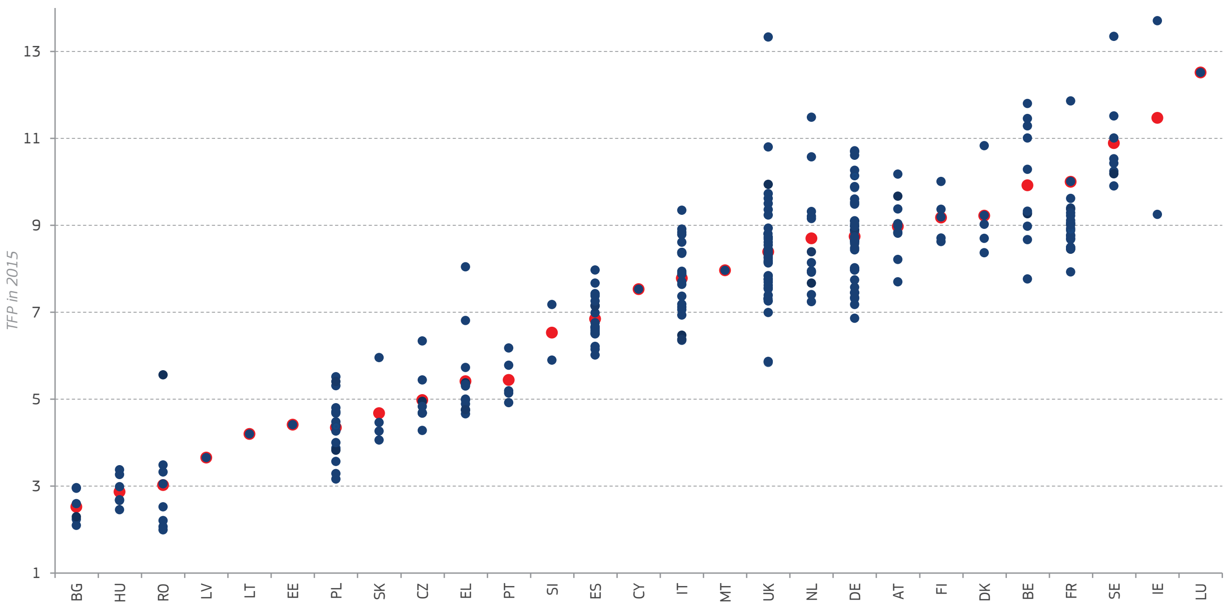


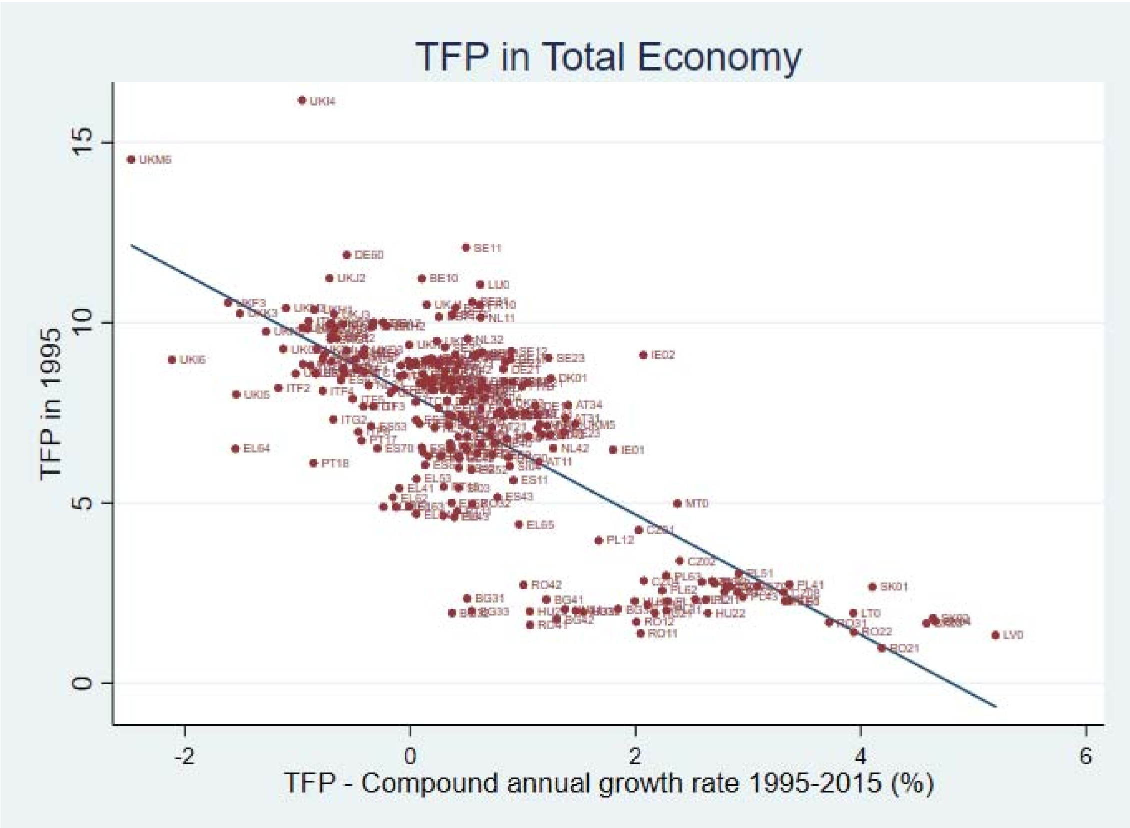
Figure 2 - TFP dispersion within countries in 2015



Note: blue dots for regions and the red dots for country averages.

In terms of temporal dynamic, the overall increase in TFP between 1995 and 2015 was around 0.24% per year (CAGR)[16], while, in the period 1995-2005, it was the triple (0.70%) followed by with a continuous slowdown in the second decade. However, despite slowing TFP growth, there has been regional convergence in TFP throughout the entire period. Figure 3 shows the negative link between regions' starting level of TFP in 1995 and their growth rate until 2015: regions where productivity levels were low at the beginning tended to experience faster TFP growth. The map in Figure 4 shows this process of convergence in TFP highlighting the catch-up of Eastern countries.

Figure 3 - Regional convergence in TFP (CARG 1995-2015)



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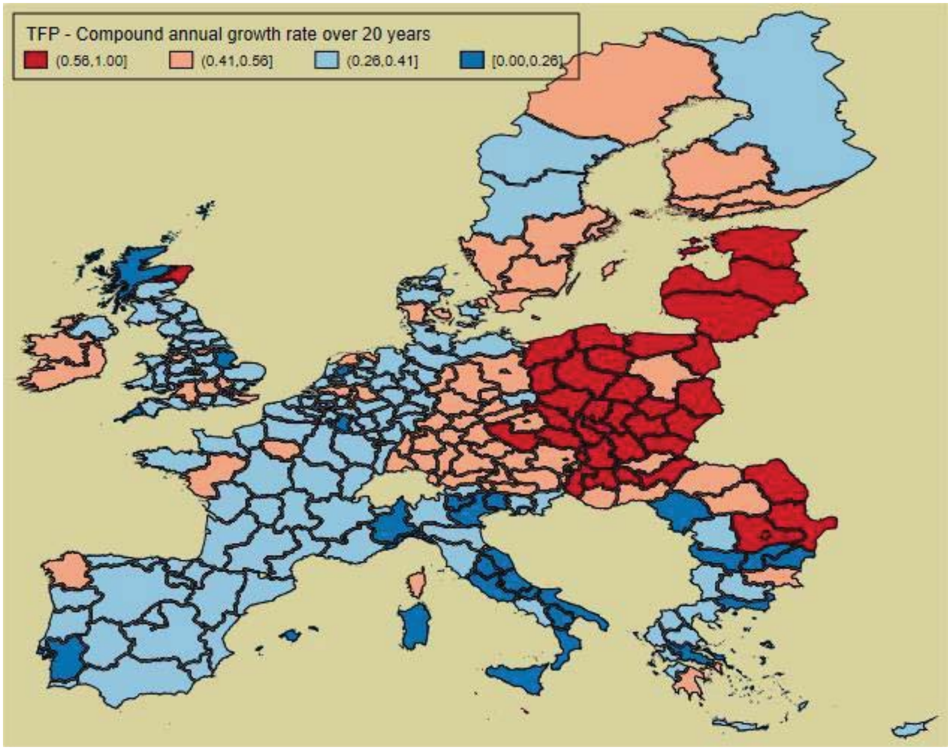
[16] We measure the average annual growth rate by the compound annual growth rate (CAGR) = $\left(\left(\frac{TFP_{r,t}}{TFP_{r,t_0}}\right)^{(t-t_0)} - 1\right) * 100$.

Figure 4- Growth of TFP from 1995 to 2015 [17]



Broadly speaking, the scatterplot (Figure 3) suggests the identification of three main types of regions following similar patterns during the period 1995-2015:

- Catching-up regions with low TFP in 1995 and high CAGR;
- Static regions with a medium-high TFP in 1995 and no increase in TFP ;
- Driving regions with medium-high TFP in 1995 and positive increase in TFP.

The determinants of the changes in TFP will be the object of the following regressions. This analysis seems relevant especially to explain the case of static regions, where the difficulties of improving productivity are likely linked to structural reasons (i.e. many Italian regions) or to the achievement of the economic maturity in some regions (i.e. in Germany), which are no longer able to achieve significant improvements in the allocation of resources. It is worth noting to recognise that the latter case is consistent with the standard hypothesis of convergence, whereas the former highlights more warning situations.

The evolution of TFP over time in the different regions determines the two phenomena already observed in many other studies[18]: a general slowdown over time and a slightly deceleration of the convergence process. In particular, Southern regions, belonging to

[17] Standardised value between 0 and 1 and regions clustered in four groups.
[18] See, for example, Ridao-Cano and Bodewing (2018).

Italy, Spain, Greece and Portugal, have experienced small or negative changes in TFP over t the last twenty years, driven by the negative performance changes of Italy. On the contrary, Eastern countries[19] present a robust growth of +2.3% per year. At the same time, the regions of core Continental countries (AT, BE, DE, FR, LU) have seen a slowdown in their average annual growth rate from 0.62% in the period 1995-2005 to 0.39% in the period 2005-2015, which is reflected in a CARG of 0.50% for the overall period. A similar dynamic has been experience by the regions in Nordic countries (DK, FI, SE, UK and IE), where the robust annual growth rate of the first period (1.18%) dramatically dropped in the second one.

This preliminary check already unveils the importance of the TFP convergence across regions and countries during the period 1995-2015. Countries (or regions) starting in 1995 with lower TFP values are those which have been growing faster in the subsequent 10 years, eventually converging towards the productivity levels of the original technological leaders.[20]

The process of technology catch-up, however, is far from being uniform across sectors. It has been especially the industry sector to have benefitted more from the technology convergence as well as (but to a lesser extent) the service sector. The convergence effect is, instead, the weakest in the agriculture sector. This analysis, even if informative, does not unveil the causality behind the process of technology catch-up. For this, we move to the regression analysis in the next section with the aim of understanding the fundamentals of the TFP catch-up dynamics. Due to data limitations, the econometric analysis is limited to the period 2000-2015.

5. The detection of spatial effects

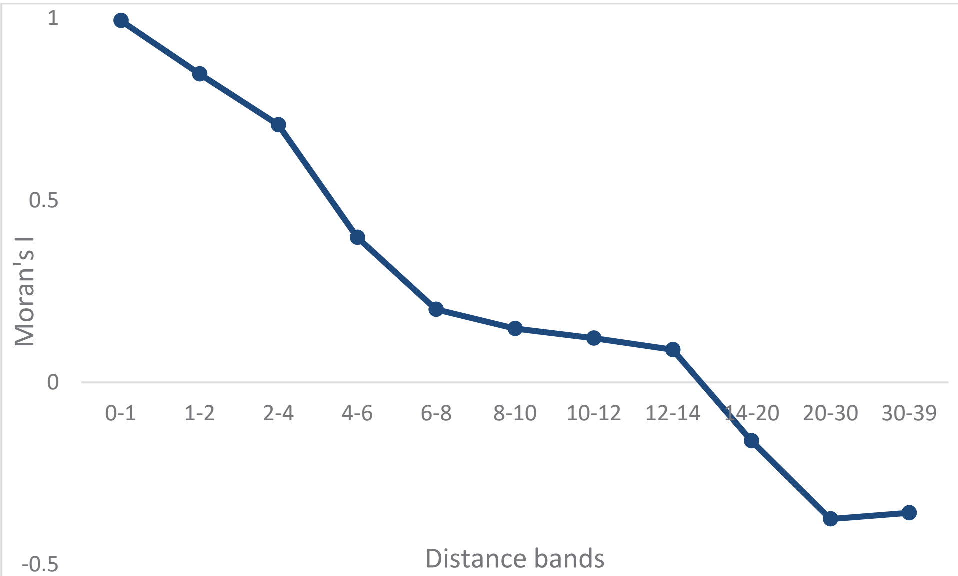
Initially we compare, in a very parsimony specification, a standard panel model with different spatial panel models. We use the starting specification of Benhabib and Spiegel (2005), where the log of human capital and the interaction term between human capital and technological gap explain the TFP growth. Our first purpose is to check the importance of taking in account the spatial dimension and to obtain preliminary information on the behaviour of the different spatial models specified by the two key variables. We choose the fixed effects model (FE) as baseline given the regional dimension of data and the result of the Hausmann test. Estimation results, reported in

[19] CZ, EE, HU, LT, LV, PL, RO, SI, SK.

[20] See also chapter 3 in Employment and Social Developments in Europe (ESDE) 2019.

Table 3 under the first column, indicate that the regional human capital does not have a significant impact on productivity growth, differently from its interaction with the TFP gap. As expected, the latter coefficient is negative because the TFP gap is specified as the ratio of the observed regions on the TFP leader. This result already supports the hypothesis of a positive impact of human capital on TFP catch-up of regions farther away from the frontier. On the other side, the non-significance of the human capital could be also explained by the lack of spatial effects in the specification of the model. In fact, the global spatial autocorrelation test[21] of the residuals confirms the presence of spatial correlation. The same indication is provided by the analysis of the dependent variable, the annual growth in total factor productivity. The Moran's I spatial correlogram in Figure 3 shows, for the year 2015, a strong positive correlation in productivity growth between each region and its neighbour that sharply decreases with the distance.

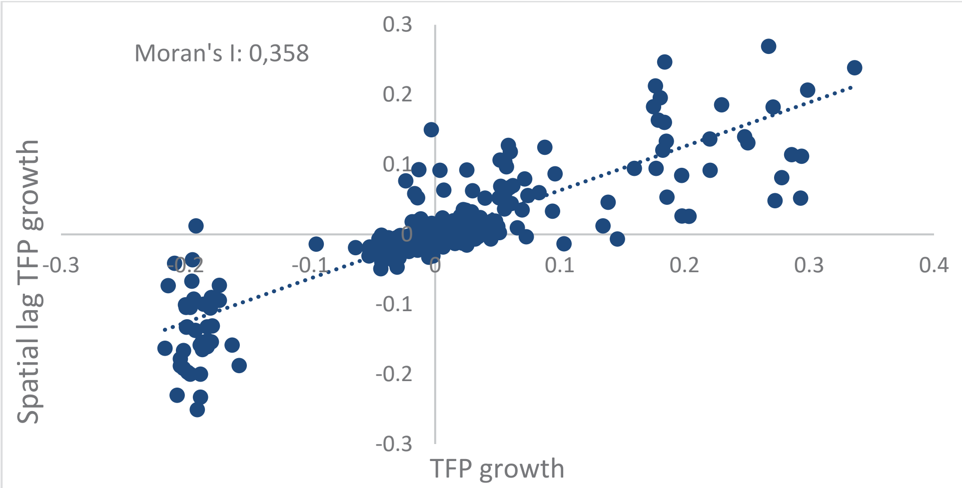
Figure 5 – Moran's Index correlation in TFP growth between regions in 2015[22])



The Moran's Index scatterplot (Figure 6) highlights the positive correlation between the TFP growth and its spatial lag.

[21] Based on the Moran's Index.
[22] The longest standardised distance is 39 units.

Figure 6 – Moran's Index scatterplot of TFP growth (years 2015)



Indeed, our basic results seem to support this hypothesis: the set of spatial models in Table 3 shows high statistical significant coefficients for human capital and different types of spatial terms. In fact, the coefficient of human capital (HC) is significant in all the specifications, pointing to the agglomeration of human capital in most dynamic regions, as well as the spatial lag term of TFP growth (rho) and the spatial error term (Lambda). The presence of spatial dependence is immediately spotted by the basic spatial models: the spatial autoregressive model (SAR), the spatial error model (SEM) and the spatial autoregressive combined model (SAC). The spatial lag terms of the explicative variables are also significant. The spatial lag of x model (SLX), the spatial Durbin model (SDM), the spatial Durbin error model (SDEM) and the general nesting spatial model (GNS) show that the spatial lag of human capital enters with a negative coefficient, indicating a negative spillover effect of human capital of neighbouring regions. This is to say that the growth in productivity of region *i* will be negatively associated to the accumulation of human capital in the neighbouring regions *j*. The more the accumulation of human capital in surrounding regions and the lower will be the growth of the examined region. This result argues, then, for the polarization of human capital accumulations in specific more productive dynamic areas and regions.

At the same time, each region benefits from TFP growth of close regions as suggested by the positive rho coefficients. The result is interesting since it seems to point to the fact that regions which have accumulated more human capital are indeed growing faster than others as well as their neighbour through TFP growth spillovers. One reason may be the increase in the market size of the center (the most dynamic regions), which would benefit all the regions in the area.

Concerning the spatial lagged term of TFP catch up, the positive coefficient suggests that, because neighbouring regions likely share a similar level of technological development, the benefit from the imitation process is lower than in case of distant regions. In other words, peripheral regions with a low technological level largely benefit from far central regions, catching-up faster to the technology frontier by means of higher growth rates, but are not necessarily also benefitting from geographically close regions.

Table 4 extends the basic model including Krugman specialization index as control variable and expenditure in Research & Development. This specification represents an augmented version of the Benhabib and Spiegel (2005) model, which did not test the role played by R&D expenditure or economic specialization.

The idea is to check whether the expenditures in R&D are actually driving the results in Table 3 and if they may represent drivers of endogenous technology growth. Previous results shown are robust to the introduction of R&D as an additional covariate. The coefficient (and statistical significance) of human capital, of its interaction and of their spatial lags change only slightly, confirming the robustness of the initial model. In addition, the R&D expenditure and its spatial lag seems to play a positive role on TFP growth.

Table 5 includes the quality of institutions comparing the spatial autoregressive model (SAC) with pooled and fixed effect models. The impact of the EQI on TFP is positively, but, although always with the correct sign, it is significant only in the non-spatial models. The sub-index likely tend to be correlated with each other. Disaggregating the overall index into the three main pillars, the most important dimensions result to be the effectiveness, voice and accountability (quality of government), while the rule of low is significant only in the pooled model. These findings are broadly in line with previous literature.[23] The human capital and the interaction term continue to be highly significant, while, surprisingly, the R&D expenditure does not seem to be significant.

Table 6, making use of the spatial autoregressive model, disentangles the direct effect of each variable from its indirect effect on TFP growth, highlighting the strategic and direct role played by the human capital, notably due to its effect and the interaction with

[23] For example, see Annoni and Catalina-Rubianes (2016) and Rodríguez-Pose and Ganau (2019).

the technological gap of the region. The importance of human capital is confirmed by Kukuvec (2018), who investigates the role of human capital and technology spillovers on regional total factor productivity growth for 569 regions in 30 countries between 1980 and 2005.

Table 3: Comparison of basic models (Dep. variable: TFP growth) – Total economy from 2000 to 2015

	FE	**SAR**	**SEM**	**SAC**	**SLX**	**SDM**	**SDEM**	**GNS**
HC	0.0294	0.0549***	0.1476***	0.1332***	0.2210***	0.1282***	0.1250***	0.0911**
	(0.0322)	(0.0154)	(0.0337)	(0.0360)	(0.0499)	(0.0379)	(0.0427)	(0.0407)
HC_gap	-0.1826***	-0.0607***	-0.2582***	-0.2662***	-0.2525***	-0.2712***	-0.2852***	-0.2940***
	(0.0120)	(0.0066)	(0.0151)	(0.0154)	(0.0209)	(0.0158)	(0.0160)	(0.0147)
rho		0.9572***		0.9409***		1.6323***		1.0950***
		(0.0106)		(0.0149)		(0.0239)		(0.0175)
lamba			1.6170***	0.9464***			1.6313***	2.3502***
			(0.0230)	(0.0134)			(0.0237)	(0.0332)
W*HC					-0.4578***	-0.0996	-0.2204**	-0.0883
					(0.0934)	(0.0710)	(0.1008)	(0.0572)
W*HC_gap					0.3343***	0.3340***	0.2573***	0.3031***
					(0.0486)	(0.0368)	(0.0541)	(0.0272)
Log lik.	8023.843	7738.386	8900.714	7840.686	8943.179	8906.108	8913.518	9210.516
Aic	-16011.69	-15468.77	-17793.43	-15671.37	-17876.36	-17800.22	-17815.04	-18407.03
Bic	-15897.42	-15443.36	-17768.02	-15639.61	-17844.60	-17762.10	-17776.92	-18362.57
Wald	36.64	8330.77	294.79	159.31	4278.86	4961.31	324.05	4370.02
Wald spatial		8212.90	4946.39	47.61	9572.84	4766.86	4768.27	10230.13
Regions	265	265	265	265	265	265	265	265
N	4240	4240	4240	4240	4240	4240	4240	4240

Region and year fixed effects included; years from 1996 to 2015. Intercepts not reported.
Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Comparison of augmented models (Dep. variable: TFP growth) – Total economy from 2000 to 2015

	FE	**SAR**	**SEM**	**SAC**	**SLX**	**SDM**	**SDEM**	**GNS**
HC	0.0557*	0.0679***	0.1550***	0.1493***	0.3022***	0.1815***	0.1719***	0.1109***
	(0.0325)	(0.0165)	(0.0344)	(0.0364)	(0.0501)	(0.0384)	(0.0435)	(0.0412)
HC_gap	-0.1859***	-0.0633***	-0.2567***	-0.2638***	-0.2676***	-0.2787***	-0.2828***	-0.2939***
	(0.0120)	(0.0066)	(0.0151)	(0.0154)	(0.0206)	(0.0158)	(0.0161)	(0.0147)
R&D	0.0083***	0.0062***	0.0038*	0.0063***	0.0074***	0.0041*	0.0050**	0.0039**
	(0.0020)	(0.0018)	(0.0021)	(0.0020)	(0.0027)	(0.0021)	(0.0021)	(0.0019)
KSI	0.0928***	0.0831***	0.0598***	0.0655***	0.0465*	0.0404**	0.0455**	0.0469**
	(0.0210)	(0.0185)	(0.0204)	(0.0197)	(0.0267)	(0.0205)	(0.0209)	(0.0192)
rho		0.9567***		0.9402***		1.6134***		1.1037***
		(0.0107)		(0.0151)		(0.0234)		(0.0186)
lamba			1.6136***	0.9443***			1.3692***	2.3563***
			(0.0230)	(0.0140)			(0.0160)	(0.0330)
W*HC					-0.7150***	-0.3567***	-0.3160*	-0.2633***
					(0.1116)	(0.0856)	(0.1795)	(0.0944)
W*HC_gap					0.2633***	0.3008***	0.2608***	0.3072***
					(0.0480)	(0.0368)	(0.0813)	(0.0273)
W*R&D					0.1042***	0.0609***	0.0559***	0.0307*
					(0.0131)	(0.0100)	(0.0190)	(0.0166)
W*KSI					1.1657***	0.3725***	0.7212***	0.1373
					(0.1256)	(0.0969)	(0.1851)	(0.1330)
Log lik.	8041.491	7754.225	8906.549	7915.430	8953.337	8937.408	8890.076	9217.264
Aic	-16042.98	-15496.45	-17801.10	-15812.86	-17892.67	-17854.82	-17760.15	-18412.53
Bic	-15916.02	-15458.34	-17762.98	-15755.69	-17848.21	-17791.29	-17696.63	-18342.65
Wald	35.00	8202.10	307.27	317.75	4216.37	5315.38	341.02	4106.65
Wald spatial		8036.05	4942.33	145.47	9076.04	5021.75	7908.64	9919.42
Regions	265	265	265	265	265	265	265	265
N	4240	4240	4240	4240	4240	4240	4240	4240

Region and year fixed effects included; years from 2000 to 2015. Intercepts not reported. Standard errors in parentheses.
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The quality of institutions (Dep. variable: annual TFP growth) – Total economy 2010 and 2013

	Pooled	**Pooled**	**Pooled**	**Pooled**	**FE**	**FE**	**SAC**	**SAC**
HC	0.0807***	0.0756***	0.0803***	0.0752***	0.2672***	0.3020***	0.2591***	0.2910***
	(0.0160)	(0.0163)	(0.0160)	(0.0163)	(0.0850)	(0.0877)	(0.0861)	(0.0852)
HC_gap	-0.0230***	-0.0247***	-0.0217***	-0.0234***	-0.4571***	-0.4529***	-0.4490***	-0.4441***
	(0.0036)	(0.0038)	(0.0037)	(0.0038)	(0.0373)	(0.0375)	(0.0385)	(0.0381)
EQI	0.0003***	0.0003***			0.0003*		0.0003	
	(0.0001)	(0.0001)			(0.0002)		(0.0002)	
R&D		0.0016		0.0016	0.0034	0.0041	0.0038	0.0047
		(0.0010)		(0.0010)	(0.0045)	(0.0045)	(0.0045)	(0.0044)
Low Corruption			-0.0002	-0.0002		-0.0003		-0.0003
			(0.0001)	(0.0001)		(0.0003)		(0.0003)
Rule of law			0.0003*	0.0003*		-0.0001		-0.0001
			(0.0002)	(0.0002)		(0.0002)		(0.0002)
Quality gov.			0.0003*	0.0003*		0.0006***		0.0006***
			(0.0001)	(0.0001)		(0.0002)		(0.0002)
rho							0.2712	0.3234
							(0.3850)	(0.3435)
lamba							-0.0133	-0.2697
							(0.6713)	(0.5679)
Log lik.	1238.569	1239.902	1240.426	1241.793	1539.369	1545.496	678.840	681.975
Aic	-2469.14	-2469.80	-2468.85	-2469.59	-3068.74	-3076.99	-1343.68	-1345.95
Bic	-2452.08	-2448.48	-2443.26	-2439.73	-3047.41	-3047.14	-1313.82	-1307.56
Wald	19.26	15.15	12.33	10.76	39.71	27.90	162.11	178.87
Wald spatial							0.65	0.90
Regions	263	263	263	263	263	263	263	263
N	526	526	526	526	526	526	526	526

FE with regional fixed effects.Region and year fixed effects included in SAC. Intercepts not reported.
Standard errors in parentheses.
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Direct and indirect effects – Spatial autoregressive combined models (SAC)
Dependent variable: annual TFP growth - Total economy from 2000 to 2015

DIRECT	**(1)**	**(2)**	**(3)**	**(4)**
HC	0.1421***	0.1592***	0.2593***	0.2914***
HC_gap	-0.2840***	-0.2812***	-0.4494***	-0.4447***
RD		0.0066***	0.0037	0.0047
KSI		0.0698***		
EQI			0.0002	
Low Corruption				-0.0003
Rule of low				-0.0001
Quality of government				0.0005***
INDIRECT				
HC	1.6674***	1.8458***	0.0806	.1160
HC_gap	-3.3315***	-3.2609***	-0.1398	-.1770
RD		0.0773**	0.0011	.00189
KSI		0.8097**		
EQI			0.0001	
Low Corruption				-.0001
Rule of low				-.0000
Quality of government				.0002
TOTAL				
HC	1.8096***	2.0050***	0.3400*	.4074*
HC_gap	-3.6156***	-3.5422***	-0.5892*	-.6217**
RD		0.0840**	0.0049	.0066
KSI		0.8796**		
QoG			0.0003	
Corr				-.0004
Impart				-.0001
Qual				.0007*

* p < .10, ** p < 0.05, *** p < 0.01

The regression results show the substantial pattern of technology catch up across the European regions. Yet, more dynamics can be unveiled when we analyse the TFP catch up process at a more disaggregated sectoral dimension which may help us to shed some light on the specific dynamics. This will be the aim of the next section, where, as for the TFP calculation, we run the computation both with a sectoral disaggregation.

6. Sectoral disaggregation

In the previous section, our regressions were focused on the regional dimension for the whole economy, but the impact of the variables of interest, computed at this level, could hide large differences across sectors, which are likely to be of interest. In fact, the aggregate level of analysis cannot show the differences and the real dynamics of specific industries. For example, an overall positive effect of human capital on TFP growth in a region could hide effects of opposite sign on some specific industries. Further, the sectoral regressions represent an additional check for the robustness of the previous estimations at regional level.

Due to the relatively poor quality of the data on capital stock at a high disaggregation level (which may affect a correct computation of the Solow residual), we decide to keep a basic six sectors disaggregation: 1) Agriculture, 2) Industry, 3) Construction, 4) Wholesale, retail, transport, accommodation, food services, information and communication (WRTAFIC), 5) Finance and business services and 6) Non-market service.[24] In same case, the lack of data also reduce the number of regions used n the estimations.

Most of the data used in this analysis are available both at regional and sectoral level. There are only three variables that do not vary by sector, namely, the *industrial specialization index*, since it is determined by structure of the regional economy, the R&D expenditures and the proxy for the quality of institutions.[25]

While the latter is by its nature a public good and therefore potentially affecting all the sectors to the same extent, the use of the total of R&D expenditure requires some justification. First, we argue that it is an acceptable choice given the lack of more specific data by sector. Second, we consider the R&D activities as a peculiar regional feature, which is capable to influence all the sectors, directly or indirectly.

The following Table 7 presents the results for the spatial autoregressive combined model (SAC), which has been selected in order to reduce the number of tables to be

[24] These sectoral aggregations correspond to the following NACE codes: A, B-E, F, G-J, K-N and O-U.

[25] However, the quality of government data are not used in this explorative analysis at sectoral level.

reported [26] , where the sectoral results seems to be consistent with those at regional level already presented. The unobserved spatial heterogeneity plays a key role as confirmed by the positive and significant coefficients of lambda and rho.

Human capital and the interaction term between human capital and technological gap show the expected, and statistically significant, sign of their coefficients, with the exception on the human capital in Agriculture.

The coefficients of R&D expenditures are always positive, but they are significant only for the financial sector. It is however worth noticing that the coefficient for Industry is not significantly different from zero, but this result is consistent with Manca and Piroli (2011), where R&D expenditure was found to be significant only for High-tech manufacturing sector.

The effect of the industrial specialization is positive for the Non-market sector and not statistically different from zero for the other sectors.

Table 7 – Spatial autoregressive combined model (SAC) by sector 2000-2015 (Dep. var.: annual TFP growth)

	Agric.	Industry	Constr.	Service (WRTAFIC)	Financial Service	Non-Market Services
HC	0.0102	0.0314***	0.0245**	0.0083*	0.0237***	0.0262***
	(0.0143)	(0.0086)	(0.0100)	(0.0044)	(0.0047)	(0.0033)
HC_gap	-0.5583***	-0.3318***	-0.2507***	-0.2148***	-0.1617***	-0.1407***
	(0.0305)	(0.0167)	(0.0152)	(0.0123)	(0.0095)	(0.0086)
R&D	0.0121	0.0042	0.0065	-0.0005	0.0072**	0.0010
	(0.0087)	(0.0050)	(0.0058)	(0.0027)	(0.0029)	(0.0020)
KSI	-0.0346	-0.0526	0.0583	0.0093	-0.0194	0.0830***
	(0.0991)	(0.0477)	(0.0557)	(0.0297)	(0.0335)	(0.0228)
rho	0.8422***	0.9238***	0.9328***	0.9315***	0.9296***	0.9476***
	(0.0377)	(0.0205)	(0.0182)	(0.0178)	(0.0183)	(0.0137)
lambda	0.8788***	0.9346***	0.9341***	0.9334***	0.9344***	0.9505***
	(0.0281)	(0.0171)	(0.0177)	(0.0173)	(0.0167)	(0.0127)
Log lik.	1543.337	4841.731	4331.425	5839.123	5309.362	6778.763
Aic	-3072.67	-9669.46	-8648.85	-11664.25	-10604.72	-13543.53
Bic	-3028.98	-9626.01	-8605.34	-11620.45	-10561.23	-13499.75
Wald	893.77	2488.75	2941.21	3154.93	3010.25	5189.11
Wald spatial	1766.09	5261.04	5731.66	6012.72	6004.90	10892.27
Regions	253	262	264	257	246	256.00
N	3795	3668	3696	3855	3690	3840

[26] The other specifications present similar results and are available on request.

7. Conclusions

Technology catch-up is an important *phenomena* affecting European regions. We show that both at national, regional and sectoral level TFP convergence is taking place in Europe.

We investigated the fundamental drivers of TFP convergence by exploiting the widely cited Benhabib and Spiegel technology catch-up framework. We have analysed, in particular, the logistic diffusion function specification by interacting human capital levels (average number of years of schooling) with the TFP gap.

Due to the very likely presence of spatial dependence across our observational units we apply different spatial econometrics models to the Benhabib and Spiegel logistic specification. We observe a strong pattern of spatial dependence across European regions. In particular, human capital seems to agglomerate in specificgrowing regions igniting a virtuous circle leading to convergence and catch up. However, the growth of surrounding regions also benefits from the high-growth of leading regions. Our result show, in fact, spatial spillovers in productivity growth from the core to the periphery.

Results robustly show the importance of human capital (proxy for the absorptive capacity of each region) in the process of technology catch-up. Those regions which have higher levels of human capital are those which more than others take advantage from technology flows coming from the frontier (TFP gap). Higher is the technological gap, higher is the potential benefit for the region.

Other controls have been also introduced which modify the standard Behnabib and Spiegel formalization. Our results are, hence, robust to various measures of employment and industrial specialization which may have directly affected the growth in TFP levels. In addition, we controlled for the R&D expenditures of the regions finding a significant effect of them on productivity growth, although mixed at sectoral level.

Finally, we show that institutions, notably the quality of government, have a positive impact on productivity growth, although apparently weak. This finding is likely conditioned by the data availability of only two years. Further investigation is needed when more data will be available. In the same way, higher sector disaggregation would be envisaged.

From the policy point of view, our findings explain that the weak productivity growth in some countries, i.e. Italy, Greece and others, depends on the lack of sufficient investments in human capital and R&D, calling for the implementation of effective measures. In this light, European Commission promote several policies as the European Skills Agenda[27], which aims to ensure that the right training, the right skills and the right support are available to people in the European Union. European Social Fund[28] and the Recovery and Resilience Facility[29] also support skills' development and human capital.

Finally, the analysis suggests not underestimating the role played by the quality of local institutions. However, further analyses at sectoral level are envisaged as next step.

[27] https://ec.europa.eu/social/main.jsp?catId=1223
[28] https://ec.europa.eu/esf/home.jsp
[29] https://ec.europa.eu/info/business-economy-euro/recovery-coronavirus/recovery-and-resilience-facility_en

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