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Human Capital, R&D and Productivity Convergence of European Regions. A spatial analysis of RHOMOLO's semi endogenous growth approach.

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Abstract: The aim of the paper is to test, in the spirit of Benhabib and Spiegel (2005), the productivity (TFP) catch-up of European regions. Differences in the stock of human capital across regions are hypothesized to be the cause of differences in the speed by which follower regions converge and catch-up with the technology frontier. We find robust empirical evidence for this hypothesis. Also, we find evidence of complementarities between public R&D expenditures and human capital accumulation for which R&D impacts TFP growth as long as a critical mass for the stock of human capital is reached. The results are robust to sectoral disaggregations and to the choice of a country or sectoral specific leader in the TFP gap computation.

1. Introduction

In 1966 Richard Nelson and Edmund Phelps formalized one of the most appealing ideas in modern economic growth, that of technological catching up across countries. The idea, which is originally due to Gerschenkron (1962), is at the same time powerful and simple. Countries lagging behind the world technological frontier may reduce their gap from it by simply imitating technologies discovered in leader countries. As in Barro and Sala-i-Martin (1997) this happens since the costs of imitation in the follower country are usually lower than those of innovation at the frontier. 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.

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. More recently, the work of Benhabib and Spiegel (1994, 2005) empirically grounded the 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 study we turn our attention to the European regional dimension with the aim of testing the Benhabib and Spiegel (2005) TFP catch-up framework on 221 NUTS2 European regions for which we build a complete cross-regional database for the period 1995-2005. 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, analyze 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.

Of crucial importance for our study is, hence, acknowledging the likely presence of spatially correlated spillovers across European regions. 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 all 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 what follows we will examine RHOMOLO's dynamic semi-endogenous model over 201 European regions for the period in between 1995 and 2005. We will exploit four spatial econometric models in order to test and control for unobserved spatial heterogeneity: (i) spatial lag, (ii) spatial error, (iii) mixed-spatial model and (iv) Durbin spatial model.

Our results strongly confirm the presence of spatial dependence in productivity 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 virtous circle leading to faster convergence towards the frontier's productivity level. The effect played by R&D expenditure is instead mixed. When we analyze it at the aggregate regional level, R&D is almost never

statistically significant for productivity growth and catch-up. In order to unveil the deeper dynamics regarding the impact of R&D on productivity we propose two non-competing explanations. On the one hand, we disaggregate our sample in 11 sectors that are analyzed with four types of spatial econometrics models. Indeed the sectoral impact of R&D expenditures on productivity is more varied. The High-tech sector, as expected, is the one more benefitting (and statistically significantly so) by expenditures in R&D while other sectors may be only marginally affected by such expenditures. On the other hand, it is reasonable to think that R&D expenditures may have a significant impact on productivity only when the region's human capital is enough to permit the full exploitation of the R&D resources. We exploit the data on regional R&D investment in order to test the specific impact of R&D expenditures on the process of European productivity convergence.

Hence, if our estimates show that R&D expenditures *per se* do not immediately drive convergence in productivity levels in certain sectors (or at the aggregate regional level), we are able to show that, when regions achieve a sufficiently high level of human capital, the effect of R&D investments is found to be growth enhancing and leading to regional productivity convergence. We argue that this result has important implication for the current European 2020 policy sustaining R&D expenditures for achieving regional economic growth.

2. The empirical model

2.1 The basic assumption of the RHOMOLO semi endogenous model

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).

To be more specific, the empirical specification that we decide to use relies on the widely cited contribution 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, the specification that we propose is the following:

$$TFPGR_{r,s} = a_0 + a_1 LnH_r - b\, LnH_r \left(\frac{TFP_{r,s}}{TFP^*_{r,s}} \right) + e_{r,s} \qquad (1)$$

Where the subscripts r stand for "region" and s for "sector". 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 a_1 and through its interaction with the technology gap with the coefficient b). 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

interaction term $bLnH_r\left(\frac{TFP_{r,s}}{TFP^*_{r,s}}\right)$ proxies for the ability of region r of absorbing the technology coming from the leader region r^*. [1]

We start from the basic specification in eq. (1) to add different control variables which may be related to the speed of technology catch-up across European regions. An important determinant of the dynamics underlying technology transfers may be the average specialization of a region. On the one hand, we compute a *location quotient* as a measure of the labour specialization of a region in sector i. This index compares the number of people working in sector with the EU average. The formulation[2] is the following:

$$LQ_{i,r} = \frac{\frac{LS_{i,r}}{POP_r}}{\sum_{rr}(\frac{LS_{i,rr}}{POP_{rr}})}$$

On the other hand, following the intuition by Krugman, we build an *industrial specialization index*. The Krugman specialization index takes value zero if region i has an industrial structure identical to the rest of the EU, indicating that region i 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. The formulation is the following:

$$DIVERS_r = \sum_i \frac{X_{i,r}}{\sum_j X_{j,r}} .\log(\frac{1}{(\frac{X_{i,r}}{\sum_j X_{j,r}})})$$

Finally, a crucial factor affecting the speed of technology catch-up is likely to be the share of R&D expenditures. Relative R&D expenditures may, in fact, speed up the process of technology catch-up of those regions which more invest in research and

[1] 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 meaning that higher levels of human capital interacted with the TFP gap lead to faster TFP growth. For a discussion of the different functional form which can be used in this context see Benhabib and Spiegel (2005).

[2] We are indebted to Ferdinand Paraguas and Gert-Jan Linders for the excellent work done in the database construction for this study and for thoughtful suggestions to the early draft of this paper.

development boosting their ability of absorbing (as well of creating) new technology. R&D expenditure, therefore, may enter the specification as an additional covariate *per se* (as in specification 2 below) explaining the growth in productivity or (as in specification 3 below) as an additional factor in the interaction term with the TFP gap.

Hence, the basic empirical specification in eq. (1) will be tested against the following two alternatives:

$$TFPGR_{r,s} = a_0 + a_1 LnH_r + a_2 RD_r + a_3 LQ_{r,s} + a_4 KSI_r + b\, LnH_r \left(\frac{TFP_{r,s}}{TFP^*_{r,s}} \right) + e_{r,s} \quad (2)$$

$$TFPGR_{r,s} = a_0 + a_1 LnH_r + a_3 LQ_{r,s} + a_4 KSI_r + b\, Ln(H_r * RD_r) \left(\frac{TFP_{r,s}}{TFP^*_{r,s}} \right) + e_{r,s} \quad (3)$$

If the interpretation of the R&D coefficient is straightforward in the specification proposed in eq. (2), the interaction of R&D with Human capital and the TFP gap deserves some comments. Crucially, what we are testing in eq. (3) is the joint hypothesis that those regions which have higher levels of human capital and (contextually) have higher expenditures in R&D are those which more than others take advantage from technology flows coming from the frontier (proxied by the TFP gap). The difference between specification 2 and 3 is therefore substantial since in 2 the effect of R&D is assumed to be direct to TFP growth while in specification 3 this works through the joint effect of human capital and of technology gap.

2.2 The spatial model

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. Nothing is however said in (1) to (3) about the possible spatial dependence across the observed regions and covariates. As we mentioned in the introduction, our aim is to test for the presence of spatial dependence and to address it by making use of four spatial econometrics models, namely: (i) spatial lag, (ii) spatial error, (iii) mixed-spatial model and (iv) Durbin spatial

model. 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 (human capital, its interaction with TFP gap and the R&D expenditures and location as well as specialization indexes) 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 spatial mixed model combines the assumptions of the previous two model while the Durbin spatial augments the spatial mixed model by the spatial lags of the explanatory variables also. Especially with this last model we will be able to check the impact of, for instance, human capital or R&D expenditures on neighbouring regions and on their productivity growth and test whether spatial spillovers are taking place across regions.

3. The data

Total factor productivity at the sector level for the NUTS 2 regions in Europe is computed using standard growth accounting methodology. Data for growth accounting are based on the Cambridge Econometrics database and from Eurostat. The growth of TFP is considered over the period 1995-2005 as well as for the period in between 1991 and 2005 as a robustness check of our results.

TFP is calculated using the conventional residual approach as follows:

$$TFP_{ijt} = \exp\left\{\log\left(Y_{ijt}\right) - a \cdot \log\left(L_{ijt}\right) - \left(1-a\right) \cdot \log\left(K_{ijt}\right)\right\} \quad (4)$$

Where Y_{ijt} is real output (Gross value added) in region i for sector j at time t (t = 1995, 1992,…, 2005)[3]. K is (physical) capital stock at the regional and sectoral disaggregation

[3] GVA is provided at constant basic prices in 2000 Euros. CE converted 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. Together with information on each region's sectoral structure, and assuming that

level. L is total number of workers (labour). The figures for labour have been adjusted for hours worked. α and $(1-\alpha)$ are the factor (labour and capital) which, consistently with the Behnabib and Spiegel (2005) approach, we take to be 2/3 and 1/3 respectively.

As for R&D indicator, we will 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 public R&D expenditure as a share of regional GVA. These have been extracted from the EuroStat database.

As for the TFP calculation, we run the computation both for the overall economy and with a sectoral disaggregation. 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 3-sector disaggregation for: (i) agriculture, (ii) industry and (iii) service sector. Here below we plot the initial TFP values for the year 1995 and the subsequent annual growth rates for the period in between 1995-2005. We do so for the aggregate national economies, for the 3 specific sectors and for regions and sectors at the same time.

[Figure 1 to 8 about here]

This preliminary check already unveils the importance of the TFP convergence across regions and countries during the period 1995-2005. 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.

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

price changes over time within a particular sector are the same for all regions of a country, these allow the construction of region-specific price deflators and hence of constant-price sectoral output series at the regional level. To adjust the data for price level differences across countries, we multiply the constant-price GVA series with the 2000 national PPS (Purchasing Power Standard) exchange rates from the CE database, which also come from AMECO.

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.

4. Regression results

We start our analysis by estimating, at the regional level, the four different spatial models on a simple level equation where the TFP growth is explained by the log of human capital and its spatial lag in the Durbin model. Results, reported in Table 1, strongly indicate that the regional human capital positively impact the growth of productivity as expected with a high statistical significant coefficient. Interestingly, the Durbin model shows that also the spatial lag of human capital enters with a negative and statistical significant coefficient. The coefficient of the spatial lag of the explanatory variable argues for 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 least 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. The coefficients associated to rho (the spatial lag term) and lambda (the spatial error term) are also statistically significant pointing to the presence of spatial dependence in the observed sample.

Table 1: Comparison of Spatial Models (Dependent Variable: TFP growth 1995-2005)

	Lag	Error	Durbin	Mixed
lnh2	0.3163***	0.5848***	0.5983***	0.5933***
	(0.0632)	(0.0974)	(0.1132)	(0.0979)
Lag HK			-0.5722***	
			(0.1917)	
Intercept	-0.6990***	-1.1620***	-0.0448	-1.1202***
	(0.1410)	(0.2257)	(0.2561)	(0.2545)
rho	0.8706***		0.9123***	-0.2119
	(0.0559)		(0.0489)	(0.1524)
lambda		0.9113***		0.9536***
		(0.0490)		(0.0390)
Sq. Corr.		0.2158		
Var. Ratio		0.1919		
Log lik.	200.3171	204.5611	204.5886	205.4248
N	201	201	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

In Table 2 we test the basic TFP catch model á la Benhabib and Spiegel (2005) where the interaction of the log of human capital with the TFP gap enters as an additional regressor. Due to the way we specify the TFP gap (as the ratio of the observed regions on the TFP leader) we expect a negative coefficient associated to the interaction term meaning a positive impact of human capital on TFP catch-up of regions farther away from the frontier. Indeed, our empirical results seem to support this hypothesis. The coefficient of the interaction term (along with that of the log of human capital *per se*) are statistically significant. The spatial lag of human capital is also statistically significant pointing to the agglomeration of human capital in most dynamic regions. In column 3, the Durbin model shows a negative (and statistically significant coefficient) for the spatial lag of the interaction term pointing to considerable spillover effect of the productivity catch up across regions. In practice, those regions that are catching-up faster to the technology frontier by means of higher growth rates are also benefitting geographically close regions. The result is interesting since it seems to point to the fact that those regions which have accumulated more human capital are indeed growing faster than others (and than their neighbour) but that, at the same time, their growth would spatially spillover to neighbouring regions through other channels. One of this may be plausibly the increase in the market size of the center (the most dynamic region) of which would benefit the periphery (the least dynamic regions surrounding the center).

Table 2: Comparison of Spatial Models (Dependent Variable: TFP growth 1995-2005)

	Lag	Error	Durbin	Mixed
lnh2	0.4232***	0.6555***	0.6207***	0.3348***
	(0.0666)	(0.0931)	(0.1133)	(0.0614)
interact_o95	-0.1386***	-0.1218***	-0.0851***	-0.1213***
	(0.0267)	(0.0348)	(0.0322)	(0.0236)
wx_lnh2			-0.3544*	
			(0.2125)	
wx_interact_o95			-0.1481**	
			(0.0623)	
Intercept	-0.7647***	-1.2150***	-0.2961	-0.6017***
	(0.1391)	(0.2071)	(0.2793)	(0.1233)
rho	0.6448***		0.5682***	0.7906***
	(0.0859)		(0.1168)	(0.0825)
lambda		0.8210***		-0.4302**
		(0.0824)		(0.1828)
Sq. Corr.		0.4465		
Var. Ratio		0.2870		
Log lik.	214.3008	210.8031	221.6618	216.3959
N	201	201	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

We may then be interested to check whether the expenditures in R&D are actually driving the results in Table 2 and if they may represent an addition channel of technology spillover. In Table 3 below, we test an augmented version of the Benhabib and Spiegel (2005) model in which the expenditures in R&D are added into the empirical specification. Previous results shown in Table 2 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.

The effect of R&D on TFP catch-up, instead, seems to be surprisingly not significant or, in the worst case, negative. The same applies to the spatial lag of R&D expenditures that does not show a statistically significant coefficient. This result is in line with that presented by Manca (2011) in a companion paper. Adjusting the model for the presence of spatial dependence does not seem to change that basic results.

Table 3: Comparison of Spatial Models (Dependent Variable: TFP growth 1995-2005)

	Lag	Error	Durbin	Mixed
lnh2	0.4467***	0.7016***	0.6656***	0.7135***
	(0.0682)	(0.0961)	(0.1152)	(0.0985)
interact_o95	-0.1274***	-0.0979***	-0.0659**	-0.0924***
	(0.0276)	(0.0360)	(0.0333)	(0.0345)
rd_gdp	-0.0089	-0.0132**	-0.0119*	-0.0128*
	(0.0061)	(0.0067)	(0.0065)	(0.0066)
wx_lnh2			-0.3654*	
			(0.2219)	
wx_interact_o95			-0.1591**	
			(0.0620)	
wx_rd_gdp			-0.0042	
			(0.0175)	
Intercept	-0.8201***	-1.3223***	-0.3618	-1.3158***
	(0.1435)	(0.2142)	(0.2958)	(0.2243)
rho	0.6530***		0.5682***	-0.1733
	(0.0853)		(0.1194)	(0.1712)
lambda		0.8430***		0.9116***
		(0.0762)		(0.0716)
Sq. Corr.		0.4294		
Var. Ratio		0.2920		
Log lik.	215.3463	212.7260	223.8516	213.1496
N	201	201	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

In Table 4 below, we augment the empirical specification by controlling for the location quotient and the specialization indexes discussed above. The results on the effect of human capital and its interaction with the TFP gap are confirmed in this specification too. The spatial lag of human capital, however, seems to loose some statistical significance when the additional control variables are added to the base model. Again, R&D expenditures do not seem to impact productivity growth positively.

Table 4: Comparison of Spatial Models (Dependent Variable: TFP growth 1995-2005)

	Lag	Error	Durbin	Mixed
lnh2	0.4512***	0.7001***	0.6489***	0.3428***
	(0.0680)	(0.0930)	(0.1191)	(0.0601)
interact_o95	-0.1190***	-0.1008***	-0.0554*	-0.1010***
	(0.0285)	(0.0364)	(0.0332)	(0.0248)
rd_gdp	-0.0062	-0.0106	-0.0112*	-0.0057
	(0.0062)	(0.0068)	(0.0066)	(0.0055)
avgksi	0.1418**	0.1447**	0.0477	0.1302***
	(0.0571)	(0.0677)	(0.0676)	(0.0484)
avglq	0.0239	0.0377	0.0184	0.0122
	(0.0538)	(0.0576)	(0.0586)	(0.0484)
wx_lnh2			-0.3699	
			(0.2321)	
wx_interact_o95			-0.1444*	
			(0.0747)	
wx_rd_gdp			0.0107	
			(0.0184)	
wx_avgksi			0.3082*	
			(0.1649)	
wx_avglq			0.0379	
			(0.1829)	
Intercept	-0.9034***	-1.4098***	-0.5169	-0.6856***
	(0.1579)	(0.2215)	(0.3818)	(0.1351)
rho	0.5923***		0.4873***	0.7718***
	(0.0924)		(0.1292)	(0.0838)
lambda		0.7854***		-0.5177***
		(0.0967)		(0.1801)
Sq. Corr.		0.4927		
Var. Ratio		0.3425		
Log lik.	218.4398	215.0266	227.9391	221.3176
N	201	201	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

The regression results show (and confirm) the substantial pattern of technology catch up across the European countries and regions previously detected. Yet, more dynamics can be unveiled when we analyze the TFP catch up process at a more disaggregated sectoral dimension which may help us to shed some light on the surprising negative coefficient shown for the relative R&D expenditures. This will be the aim of the next section

5. Sectoral disaggregation. Interacting R&D, Human capital and TFP gap

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. In this section we test our previous results allowing for a disaggregation into 11 sectors: 1) Agriculture, 2) Mining and energy, 3) Low-tech manufacturing, 4) High-tech manufacturing, 5) Construction, 6) Distribution, 7) Hotel and restaurants, 8) Transport and communication, 9) Financial intermediation, 10) Business services, 11) Public sector.

Most of the data used in our analysis are available both at regional and sectoral level. There are only two variables that do not change by sector, namely, the *industrial specialization index*, since it is determined by structure of the regional economy, and public R&D expenditures.

Regard this latter, we assume that this is a public good and, therefore, potentially available for all sectors to the same extent.
In the following tables, results for the richest empirical specification are presented[4] .
For each sectors (Tables from 5 to 7) we report estimations of the spatial lag, spatial error and for the mixed model. The results of these three different models are very similar and consistent with those at regional level presented in the previous section.

The two indices of specialization are almost always positive or not statistically different from zero, except in case of Agriculture. The coefficients of R&D expenditures confirm previous estimations which showed a negative sign.

It is however worth noticing the result for High-tech manufacturing sector. In this sector, the elasticity of TFP growth with respect to R&D expenditures is positive and statistically significant pointing to the direct effect played by R&D to firms at the technology frontier.

The peculiarity of the High-tech sector is confirmed by the coefficients estimated by the Durbin model presented in Table 8 below. For this sector, differently from Low-tech manufacturing, spatial lag of human capital and R&D expenditure show positive coefficients, but only the second one is statistically significant. In fact, estimating the mixed model augmented with spatial lags of our interest, the coefficient for spatial lag of human capital becomes negative and statistically significant.

All the other variables show the expected, and statistically significant, sign of their coefficients.

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

Table 5: Sectoral comparison of Spatial Lag Models (Dependent Variable: TFP growth 1995-2005)

Sectors	1	2	3	4	5	6	7	8	9	10	11
lnh2	0.6106**	1.3030***	0.6995***	0.8733***	0.4391***	0.7474***	0.3943**	0.1856	0.0586	0.1173	0.2244***
	(0.2510)	(0.2918)	(0.2278)	(0.1352)	(0.1661)	(0.0953)	(0.1782)	(0.1422)	(0.2223)	(0.0974)	(0.0622)
rd_gdp	-0.0585***	-0.0703**	-0.0198	0.0499***	-0.0255**	0.0115	0.0203	0.0055	-0.0200	0.0173	-0.0170**
	(0.0223)	(0.0280)	(0.0242)	(0.0172)	(0.0100)	(0.0097)	(0.0168)	(0.0127)	(0.0233)	(0.0132)	(0.0071)
interact_o95	-0.3808***	-0.3961***	0.1048	-0.1081***	-0.1670**	-0.1218***	-0.3371***	-0.2969***	-0.4671***	-0.3019***	-0.1114***
	(0.0804)	(0.0805)	(0.2160)	(0.0377)	(0.0785)	(0.0352)	(0.0575)	(0.0879)	(0.0958)	(0.0372)	(0.0240)
avglq	-0.0120	-0.0042	-0.0503	-0.0413	-0.0085	0.1972***	0.0372	0.0355	0.2463***	0.0797**	0.0808***
	(0.0260)	(0.0363)	(0.0652)	(0.0361)	(0.0569)	(0.0477)	(0.0273)	(0.0384)	(0.0767)	(0.0323)	(0.0235)
avgksi	-0.5034*	-0.0897	0.6541**	0.0013	-0.1474	0.2767***	0.0045	-0.0365	0.5782***	-0.0198	0.1475**
	(0.2752)	(0.2669)	(0.3002)	(0.1076)	(0.1228)	(0.0715)	(0.1337)	(0.1023)	(0.2006)	(0.1034)	(0.0608)
Intercept	-0.6900	-2.2459***	-1.7083***	-1.7402***	-0.7351**	-1.8088***	-0.6406	-0.2111	0.0828	-0.0228	-0.4432***
	(0.5465)	(0.5940)	(0.4363)	(0.2757)	(0.3291)	(0.2261)	(0.3978)	(0.3381)	(0.4682)	(0.2121)	(0.1443)
rho	0.4917***	0.3651**	0.8681***	0.3494***	0.5533***	0.4431***	0.2469*	0.6631***	0.7616***	0.1538	0.7400***
	(0.1299)	(0.1520)	(0.0825)	(0.1144)	(0.1220)	(0.1176)	(0.1416)	(0.0974)	(0.0941)	(0.1724)	(0.0772)
Sq. Corr.	0.2314	0.3285	0.0148	0.4091	0.1679	0.4405	0.2994	0.1629	0.3102	0.3379	0.4276
Var. Ratio	0.1751	0.3158	0.4321	0.3796	0.2027	0.4851	0.3360	0.2784	0.5507	0.3635	0.5303
Log lik.	-71.3219	-94.3930	-78.7754	78.1562	52.7290	127.7092	28.5555	41.5680	-80.8326	83.4945	196.8520
N	201	196	200	200	201	201	201	201	200	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Sectoral comparison of Spatial Error Models (Dependent Variable: TFP growth 1995-2005)

Sectors	1	2	3	4	5	6	7	8	9	10	11
lnh2	0.6418*	1.5260***	1.0981**	1.0661***	0.7656***	0.9951***	0.5873***	0.4851**	0.4979	0.1707	0.5341***
	(0.3470)	(0.3762)	(0.4302)	(0.1463)	(0.2084)	(0.1305)	(0.2142)	(0.2200)	(0.4136)	(0.1559)	(0.1098)
rd_gdp	-0.0561**	-0.0574*	-0.0238	0.0489***	-0.0208	0.0070	0.0066	0.0021	-0.0203	0.0170	-0.0176**
	(0.0274)	(0.0323)	(0.0267)	(0.0141)	(0.0147)	(0.0102)	(0.0169)	(0.0152)	(0.0295)	(0.0128)	(0.0070)
interact_o95	-0.3720***	-0.4626***	0.3993***	-0.1217***	-0.2151***	-0.1681***	-0.4282***	-0.3645***	-0.5983***	-0.3508***	-0.1390***
	(0.0810)	(0.0752)	(0.1318)	(0.0414)	(0.0606)	(0.0343)	(0.0622)	(0.0716)	(0.0824)	(0.0401)	(0.0272)
avglq	-0.0040	0.0079	-0.0559	-0.0267	0.0484	0.1795***	0.0280	0.0426	0.2487***	0.0765**	0.0421
	(0.0314)	(0.0348)	(0.0688)	(0.0383)	(0.0640)	(0.0537)	(0.0289)	(0.0396)	(0.0662)	(0.0327)	(0.0271)
avgksi	-0.4872*	-0.0652	0.7997***	0.0392	-0.1382	0.3169***	0.1085	-0.0448	0.5237*	0.0001	0.1838***
	(0.2956)	(0.2881)	(0.2757)	(0.1285)	(0.1403)	(0.0961)	(0.1564)	(0.1475)	(0.2916)	(0.1120)	(0.0699)
Intercept	-0.6762	-2.6123***	-2.1522**	-2.1154***	-1.4780***	-2.2735***	-0.9851**	-0.8001	-0.4964	-0.0846	-0.9587***
	(0.7692)	(0.8308)	(1.0442)	(0.3199)	(0.4768)	(0.3041)	(0.4862)	(0.4963)	(0.9243)	(0.3444)	(0.2399)
lambda	0.4920***	0.4266***	0.9032***	0.2698	0.6894***	0.6212***	0.5335***	0.7344***	0.7733***	0.4925***	0.8577***
	(0.1364)	(0.1478)	(0.0541)	(0.1694)	(0.1187)	(0.1185)	(0.1490)	(0.0983)	(0.0996)	(0.1527)	(0.0674)
Sq. Corr.	0.1973	0.3150	0.0578	0.3859	0.1440	0.4331	0.3042	0.1819	0.3463	0.3459	0.3861
Var. Ratio	0.1245	0.2811	0.1683	0.3468	0.1785	0.4549	0.4169	0.2192	0.3160	0.4249	0.3405
Log lik.	-73.5278	-94.8441	-75.2049	75.6356	54.5174	130.2757	32.3401	44.1976	-82.6172	87.2537	198.4545
N	201	196	200	200	201	201	201	201	200	201	201

Standard errors in parentheses

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

Table 7: Sectoral comparison of Spatial Mixed Models (Dependent Variable: TFP growth 1995-2005)

Sectors	1	2	3	4	5	6	7	8	9	10	11
lnh2	0.5864**	1.0773***	1.0021**	0.6782***	0.7510***	1.0370***	0.7845***	0.4874**	0.2746	0.1894	0.5544***
	(0.2307)	(0.2902)	(0.4058)	(0.1332)	(0.2272)	(0.1422)	(0.2323)	(0.2269)	(0.3654)	(0.1682)	(0.1102)
rd_gdp	-0.0600**	-0.0789***	-0.0250	0.0521***	-0.0210	0.0071	0.0050	0.0021	-0.0231	0.0186	-0.0169**
	(0.0243)	(0.0278)	(0.0266)	(0.0112)	(0.0148)	(0.0101)	(0.0158)	(0.0152)	(0.0286)	(0.0128)	(0.0070)
interact_o95	-0.3672***	-0.3152***	0.3511**	-0.0891***	-0.2136***	-0.1755***	-0.4982***	-0.3647***	-0.5284***	-0.3656***	-0.1401***
	(0.0767)	(0.0767)	(0.1377)	(0.0279)	(0.0609)	(0.0349)	(0.0638)	(0.0718)	(0.0807)	(0.0396)	(0.0273)
avglq	-0.0167	-0.0187	-0.0576	-0.0536	0.0472	0.1729***	0.0207	0.0426	0.2589***	0.0708*	0.0387
	(0.0254)	(0.0321)	(0.0685)	(0.0358)	(0.0647)	(0.0543)	(0.0292)	(0.0396)	(0.0651)	(0.0369)	(0.0271)
avgksi	-0.4965**	-0.1170	0.7686***	-0.0143	-0.1396	0.3295***	0.1889	-0.0443	0.4878*	0.0213	0.1870***
	(0.2388)	(0.2203)	(0.2710)	(0.1021)	(0.1401)	(0.0990)	(0.1575)	(0.1481)	(0.2701)	(0.1152)	(0.0698)
Intercept	-0.6745	-1.8726***	-2.2901**	-1.3592***	-1.4464***	-2.3498***	-1.3272**	-0.8052	-0.2464	-0.1172	-0.9484***
	(0.4942)	(0.5870)	(0.9222)	(0.2665)	(0.5171)	(0.3253)	(0.5208)	(0.5107)	(0.7925)	(0.3720)	(0.2444)
rho	0.6349***	0.6398***	0.4142*	0.6129***	0.0459	-0.1647	-0.5015***	-0.0109	0.5553***	-0.2716	-0.1527
	(0.1403)	(0.1692)	(0.2114)	(0.1209)	(0.2812)	(0.2002)	(0.1733)	(0.2510)	(0.1732)	(0.1709)	(0.1755)
lambda	-0.27987	-0.4685	0.7839***	-0.0555***	0.6636***	0.7279***	0.7935***	0.7394***	0.6543***	0.654***	0.9058***
	0.2287	0.2919	0.1284	0.2078	.2065	0.1485	0.1041	0.1520	0.1529	0.1529	0.0686
Sq. Corr.	0.2382	0.3359	0.0359	0.4214	0.1445	0.4307	0.3249	0.1820	0.3326	0.3571	0.3789
Var. Ratio	0.1976	0.3330	0.2472	0.4278	0.1823	0.4255	0.4035	0.2181	0.4450	0.4002	0.3067
Log lik.	-70.7143	-93.7311	-73.3104	80.5924	54.5310	130.5768	35.5577	44.1986	-78.5064	88.4093	198.7987
N	201	196	200	200	201	201	201	201	200	201	201

Standard errors in parentheses

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

Table 8: Sectoral comparison of Spatial Durbin Models (Dependent Variable: TFP growth 1995-2005)

Sectors	1	2	3	4	5	6	7	8	9	10	11
lnh2	0.1876	1.2512**	0.7814	0.8211***	1.1038***	1.0357***	1.0645***	0.6128***	0.4328	0.3163*	0.7072***
	(0.5836)	(0.4932)	(0.5534)	(0.2176)	(0.2870)	(0.1571)	(0.2732)	(0.2211)	(0.4401)	(0.1916)	(0.1226)
rd_gdp	-0.0481*	-0.0397	-0.0232	0.0389**	-0.0196	0.0046	-0.0032	-0.0001	-0.0267	0.0213	-0.0225**
	(0.0246)	(0.0280)	(0.0280)	(0.0186)	(0.0127)	(0.0117)	(0.0183)	(0.0147)	(0.0247)	(0.0157)	(0.0088)
wx_lnh2	1.1839	0.7608	-0.0089	0.2323	-1.4650***	-0.7363**	-1.1179**	-0.7444	-0.8151	-0.3043	-0.8948***
	(0.9985)	(1.0560)	(0.9976)	(0.4854)	(0.4066)	(0.3210)	(0.4783)	(0.4628)	(0.8516)	(0.3433)	(0.2179)
wx_rd_gdp	-0.0970	-0.2851**	-0.0205	0.0831**	-0.0326	0.0599**	0.1233***	0.0405	0.0703	-0.0224	0.0122
	(0.0811)	(0.1123)	(0.0847)	(0.0341)	(0.0427)	(0.0283)	(0.0421)	(0.0406)	(0.0748)	(0.0396)	(0.0230)
interact_o95	-0.3681***	-0.4190***	0.4859	-0.0460	-0.2116*	-0.1759***	-0.5741***	-0.3624***	-0.5821***	-0.4174***	-0.1266***
	(0.0834)	(0.0895)	(0.3318)	(0.0720)	(0.1203)	(0.0471)	(0.1233)	(0.1167)	(0.1061)	(0.0489)	(0.0482)
wx_ interact_o95	-0.1797	-0.0079	-0.7193**	-0.1500	-0.0442	0.2126**	0.5092**	0.2885	0.3753*	0.4340***	0.0011
	(0.2313)	(0.2515)	(0.3174)	(0.1082)	(0.1645)	(0.0993)	(0.2149)	(0.2012)	(0.2104)	(0.1156)	(0.0718)
avglq	-0.0445	-0.0059	-0.0807	-0.0494	0.0804	0.1491***	-0.0046	0.0390	0.2724***	0.0312	0.0247
	(0.0362)	(0.0429)	(0.0670)	(0.0389)	(0.0741)	(0.0484)	(0.0252)	(0.0330)	(0.1008)	(0.0411)	(0.0270)
avgksi	-0.4019	-0.3037	0.6280	0.0238	-0.1944	0.2787**	0.4036**	-0.1339	0.0569	0.1452	0.1398*
	(0.3132)	(0.3894)	(0.4177)	(0.1349)	(0.2184)	(0.1102)	(0.1749)	(0.2004)	(0.4296)	(0.1245)	(0.0768)
wx_avglq	0.0650	-0.0058	0.0789	-0.0402	-0.5269***	0.0809	0.0627	-0.0633	-0.2049	0.0415	0.2147**
	(0.0840)	(0.1137)	(0.2088)	(0.1582)	(0.1394)	(0.1659)	(0.0724)	(0.1583)	(0.1793)	(0.0618)	(0.0877)
wx_avgksi	-0.6827	0.2178	-0.0639	-0.0853	-0.0168	0.2779	-0.7319**	0.6158	2.2072	-0.3333	0.1638
	(0.7202)	(0.8209)	(0.7166)	(0.3928)	(0.4199)	(0.2837)	(0.3642)	(0.5968)	(1.3749)	(0.3059)	(0.2003)
Intercept	-1.9874*	-3.4701**	-1.5977	-2.0284***	1.6662***	-1.1737**	0.1386	0.1966	0.3552	-0.0873	0.2966
	(1.1991)	(1.4129)	(1.3404)	(0.6543)	(0.5559)	(0.5166)	(0.6715)	(0.7591)	(1.2072)	(0.4797)	(0.2766)
rho	0.3741**	0.2441	0.7953***	0.1831	0.4543***	0.5262***	0.3585**	0.7311***	0.7292***	0.3900**	0.7526***
	(0.1562)	(0.1649)	(0.1001)	(0.1456)	(0.1450)	(0.1332)	(0.1398)	(0.1075)	(0.1066)	(0.1575)	(0.0821)
Sq. Corr.	0.2516	0.3816	0.3436	0.4275	0.3061	0.4868	0.4143	0.1912	0.3776	0.4002	0.4991
Var. Ratio	0.2315	0.3599	0.2984	0.4346	0.2806	0.5173	0.4119	0.2241	0.5690	0.4026	0.5469
Log lik.	-69.4853	-88.8927	-71.4478	82.1904	64.5479	136.4298	45.1044	45.9533	-74.5619	93.5437	208.7834
N	201	196	200	200	201	201	201	201	200	201	201

Standard errors in parentheses

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

Table 9: Sectoral comparison of Spatial Mixed Models with lags HC and R&D (Dependent Variable: TFP growth 1995-2005)

Sectors	1	2	3	4	5	6	7	8	9	10	11
lnh2	0.3346	0.8881	0.9497**	0.8389***	1.1053***	1.0284***	0.8822***	0.6904***	0.6672	0.2169	0.6215***
	(0.4942)	(0.5694)	(0.4721)	(0.2394)	(0.2535)	(0.1663)	(0.2625)	(0.2581)	(0.4885)	(0.2201)	(0.1369)
lags_lnh2	0.5320	0.8447	0.1736	-0.2988	-1.1350**	-0.2646	-1.0433*	-0.9244*	-1.0895	-0.1151	-0.7750***
	(0.8036)	(0.8844)	(1.0595)	(0.4202)	(0.4544)	(0.3979)	(0.5771)	(0.5388)	(0.9015)	(0.4325)	(0.2279)
rd_gdp	-0.0478*	-0.0208	-0.0240	0.0436***	-0.0257*	0.0073	0.0067	0.0013	-0.0258	0.0185	-0.0198***
	(0.0276)	(0.0318)	(0.0270)	(0.0142)	(0.0144)	(0.0103)	(0.0157)	(0.0152)	(0.0285)	(0.0129)	(0.0070)
lags_rd	-0.0613	-0.2943***	0.0171	0.0312	-0.0395	0.0666**	0.1487***	0.0399	0.0356	0.0137	0.0062
	(0.0724)	(0.0819)	(0.0851)	(0.0410)	(0.0428)	(0.0303)	(0.0489)	(0.0462)	(0.0831)	(0.0397)	(0.0196)
interact_o95	-0.3683***	-0.3491***	0.3575**	-0.0864***	-0.2014***	-0.1697***	-0.4893***	-0.3812***	-0.5374***	-0.3639***	-0.0952***
	(0.0778)	(0.0685)	(0.1388)	(0.0326)	(0.0576)	(0.0351)	(0.0642)	(0.0721)	(0.0809)	(0.0400)	(0.0210)
avglq	-0.0174	-0.0206	-0.0586	-0.0456	-0.0088	0.1744***	0.0181	0.0386	0.2530***	0.0693*	0.0667***
	(0.0256)	(0.0305)	(0.0719)	(0.0372)	(0.0680)	(0.0544)	(0.0285)	(0.0396)	(0.0654)	(0.0376)	(0.0251)
avgksi	-0.5324**	-0.3258	0.7705***	0.0197	-0.1693	0.3453***	0.2177	-0.0297	0.4845*	0.0245	0.1384**
	(0.2440)	(0.2185)	(0.2741)	(0.1094)	(0.1295)	(0.0967)	(0.1523)	(0.1464)	(0.2686)	(0.1151)	(0.0562)
Intercept	-1.2362	-2.9535***	-2.5753	-1.0905*	0.4213	-1.8350**	0.5742	0.7815	1.2998	0.0624	0.3988
	(0.9551)	(1.0406)	(1.9946)	(0.5583)	(0.7178)	(0.7612)	(1.0606)	(1.0093)	(1.4933)	(0.7512)	(0.2778)
rho	0.6180***	0.5628***	0.3998*	0.5989***	0.3764	0.0046	-0.2380	0.1648	0.5855***	-0.2401	0.8431***
	(0.1515)	(0.1545)	(0.2254)	(0.1734)	(0.2641)	(0.2353)	(0.2049)	(0.2842)	(0.1657)	(0.1894)	(0.0993)
lambda	-0.2483	0.3674***	0.7942***	-0.4809	0.3027	0.6403***	0.6444***	0.6778***	0.4752**	0.6350***	-0.1983
	(0.2416)	(0.0198)	(0.1284)	(0.2946)	(0.3447)	(0.1803)	(0.1509)	(0.1909)	(0.1958)	(0.1678)	(0.3097)
Sq. Corr.	0.2335	0.3902	0.0377	0.4198	0.2238	0.4419	0.3657	0.1674	0.3271	0.3572	0.3823
Var. Ratio	0.2012	0.3772	0.2558	0.4298	0.2060	0.4481	0.4177	0.1943	0.4284	0.3985	0.6607
Log lik.	-70.2615	-87.2668	-73.2704	81.1032	58.2342	132.9031	40.5337	45.7554	-77.7631	88.4869	205.1806
N	201	196	200	200	201	201	201	201	200	201	201

Standard errors in parentheses
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$

[WORK IN PROGRESS]

6. 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 analyzed, in particular, the logistic diffusion function specification by interacting human capital levels (average number of years of schooling) with the TFP gap.

Results robustly show the importance of human capital (proxying for the absorptive capacity of each region) in the process of technology catch-up. 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. Also, we controlled for the average R&D expenditures of the regions finding a weak effect of them on productivity growth. For this reason we re-specified the TFP catch-up framework in order to allow for the interaction among human capital, R&D and the gap in technology. Results for the region economies show that R&D plays a positive role on TFP growth when a certain level of human capital has been achieved by the region. The effect is however mixed when we look at the sectoral disaggregation and stronger for the agriculture and service sectors.

Also the effect of R&D expenditures is shown to be sectoral specific, with a stronger and statistically significant impact in the high-tech and a mixed impact in the other remaining sectors.

Due to the very likely presence of spatial dependence across our observational units we apply four 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 fat-growing 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 which go from the core to the periphery.

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References

[1] Abramovitz, M., 1986. Catching up, forging ahead, and falling. Behind. Journal of Economic History 46, 385–406.

[2] Audretsch, D. 1998. Agglomeration and the Location of Economic Activity. Oxford Review of Economic Policy 14, 18-29.

[3] Bayoumi, T., Coe, D. and E. Helpman(1999). R&D Spillovers and global Growth. Journal of International Economics, 47, 399-428.

[4] Barro, R., and Sala-i-Martin, X. (1997), Technological Diffusion,Convergence and Growth, Journal of Economic Growth, 1, 1-26

[5] Barro, R.J. and X. Sala-i-Martin (1995). Economic Growth. 1st ed., New York (McGraw-Hill).

[6] Benhabib, J., Spiegel, M., 2005. Human capital and technology diffusion. In: Aghion, P., Durlauf, S. (Eds.), Handbook of Economic Growth. Elsevier.

[7] Coe, D., Helpman, E., Hoffmaister, A., 2008. International R&D Spillovers and Institutions. CEPR Discussion Papers 6882, C.E.P.R. Discussion Papers.

[8] Jones, C.I. (1995). R&D-Based Models of Economic Growth, Journal of Political Economy, 103, 759-784.

[9] Howitt, P. 2000. "Endogenous Growth and Cross-Country Income Differences," American Economic Review, American Economic Association, vol. 90(4), pages 829-846, September.

[10] Keller, W. (1998). Are International R&D Spillovers Trade-Related? Analyzing Spillovers Among Randomly Matched Trade Partners. European Economic Review, 42, 1469-1481.

[11] Nelson, R., Phelps, E., 1966. Investment in humans, technological diffusion, and economic growth. American Economic Review 56, 69–75.