Determinants of regional productivity growth in Europe: An empirical analysis

Tatyana Bulavskaya[1], Henri L. F. de Groot[2,*], Gert-Jan M. Linders[2] and Ferdinand J. Paraguas

[1] TNO, Delft, The Netherlands
[2] VU University, Department of Spatial Economics, Amsterdam, The Netherlands

Abstract:
Understanding the sources of regional differences in productivity and the possibilities for mitigating them is at the heart of the debate on European regional economic policy. This study presents an empirical analysis of the determinants of regional productivity growth in Europe, using the most recent Cambridge Econometrics regional database supplemented with EuroStat data on education and R&D. We generate empirical estimates of a reduced-form equation explaining regional total factor productivity growth. The empirical model, based on innovation and catch-up to the technology frontier as engines of growth, allows for a steady state where productivity levels differ, but growth rates converge. We test whether aggregate regional productivity growth in a region depends on its level of human capital, the investments in R&D, and the productivity gap with the technology frontier. Results show that these variables affect regional productivity growth and that the effects are interrelated. Apart from a technology gap, absorptive capacity is important to realize catch-up. Results for agriculture, industry and services sectors reveal different patterns of regional productivity growth. The estimated model also features stable dynamic properties in response to an exogenous shock.

Keywords: Semi-endogenous Growth, Regional Convergence, International Transfer of Technology, human capital, R&D.
JEL codes: O18, O33, R12

* Corresponding author: hgroot@feweb.vu.nl. Department of Spatial Economics, De Boelelaan 1105, NL-1081 HV, Amsterdam, the Netherlands.

1. Introduction

Countries and regions differ in their stage of development, as reflected in per capita income and total factor productivity. Apart from differences in levels, productivity growth performance differs substantially as well. Latecomers in development may benefit from a larger potential for technology transfer, and have to build up their physical capital intensity of production. This suggests that convergence in productivity is likely, at least to some extent. Then again, for latecomers to catch-up, the initial productivity gap should not be too large, and sufficient absorptive capacity for knowledge transfer is prerequisite.

Understanding the different development paths of regions is of importance for policy makers. Growth and convergence are important elements in fostering cohesion within the EU, as they can help reduce socio-economic vulnerability and disparities between countries or regions. Which policy measures are needed and effective, if any, to foster regional growth and catch-up to the frontier? To what extent will regional productivity levels and growth rates converge? This paper intends to contribute to our understanding of variation in productivity growth, by empirical investigation of a number of potential determinants of growth in productivity over the period 1997-2008. We focus on the effects of regional innovative activity (affected by R&D intensity, and human capital) and regional technology adoption (proxied by interacting relative productivity and absorptive capacity, reflected by human capital) on regional growth in European regions.

The paper is organized as follows. Section 2 provides background on some relevant previous studies of European regional productivity growth. Section 3 presents the model, empirical specification and some descriptive statistics on productivity growth, and describes data and variables used. Section 4 presents the empirical results and Section 5 concludes with a view towards further research.

2. Background

The empirical literature on determinants of economic growth contains two related strands that are important for our purposes. First, the growth regression literature – grounded in the neo-classical growth model – investigates the determinants of growth in per capita income. In this literature, the concept of (conditional) convergence to a (uniform) steady state growth rate is central (see Baumol, 1986; Barro, 1991). A lower initial income implies a higher subsequent growth. Though often applied mostly to cross-country (panel) datasets, applications to regional growth have already emerged early on (e.g., Barro et al., 1991). A second strand of literature – rooted in the more recent endogenous growth theories – focuses on technology transfer as engine of growth, and investigates growth in a measure of productivity more explicitly linked to technology, total factor productivity (Benhabib and Spiegel, 2005). Instead of convergence, this latter framework often refers to catch-up growth towards the technological leader. A recent application of this framework to regional growth is Cameron et al. (2005), for the UK.

Although both strands of empirical models emerged separately and are conceptually different, they can be nested. Under certain conditions, both the first and second type of model frameworks are compatible with steady state properties, in which long run productivity levels are endogenous while long run productivity growth rates tend to equalize. As (growth in) total factor productivity is one important determinant of (growth in) per capita income, it is empirically difficult to distinguish (out-of-steady-state) convergence and catch-up growth due to technology transfer in models using initial income or productivity levels.

Given this pragmatic stance, we discuss insights from a somewhat eclectic literature on regional growth. Some studies focus on convergence in per capita incomes, others on technology transfer. In the latter, some use TFP and others per capita income as productivity measure. Still, we think it is important to be as clear cut as possible in our own empirical analysis. Hence, we will comment on differences in approach between earlier studies and the present study where relevant.

Understanding growth performance of European countries and regions is important for regional policy at both the national and European level. Niebuhr and Schlitte (2004) investigate patterns of convergence in income levels across European countries and regions over various time periods up to 2000. They estimate growth regressions at the regional level, focusing on the initial income effect to estimate existence and speed of convergence. They conclude that convergence occurs, but its speed has declined well below the conventional 2% level in recent decades. Interestingly, the speed of convergence at the national level has increased substantially in the second half of the 1990s, whereas intra-country convergence between regions was largely absent (i.e., when controlling for country-specific effects in growth performance). They hint at increased spatial interaction (trade and FDI) as potential explanation for why the speed of convergence differs across time periods. To explain differences between cross-country and cross-region convergence, they suggest that processes of agglomeration may imply that most of the catching-up of poor member states concentrates in urban regions. In their words, this poses an equity-efficiency dilemma to regional policy. For example, the convergence objective of European Cohesion Policy targets the poorer regions in member states, while dynamic catch-up processes between member states may actually originate in relatively richer regions.

Tselios (2009) shows the importance of explicitly controlling for heterogeneity in regional characteristics for better understanding which forces drive convergence at the regional level. He proposes a dual perspective on regional cohesion, by investigating the existence of convergence in income per capita and in intra-regional income inequality across regions for the period 1995-2000. As in Niebuhr and Schlitte (2004), OLS regression does not show any unconditional convergence in per capita incomes between regions, even if not controlling for country-specific effects. Regional income inequality does show unconditional convergence over time. However, evidence shows that conditional convergence of income per capita across European regions exists, once controlling for regional differences in educational attainment, unemployment and sectoral composition. The analysis shows that industrial or services oriented regions grow faster, offering support for agglomeration effects as important for growth. The effect of various measures of human capital differs according to the estimation method used. Both cross-section and pooled OLS (using two-year panel periods) show a negative effect of secondary education attainment; within-groups estimation (regional fixed effects) and spatial econometric estimation (including fixed effects) show a positive effect on growth. Unemployment has a consistently negative effect (though not always significant). Including spatially lagged income growth in the model turns out to be an important control factor in yielding conditional income convergence. This provides support for the importance of location and spatial interaction for bringing about convergence.

The literature discussed so far focuses on investigation of the existence of convergence or catch-up in income per capita levels. Theoretically, convergence reflects transition towards a steady state, which relates to accumulation of reproducible capital (physical or human capital) intensities subject to diminishing returns. Catch-up growth reflects diffusion of knowledge via technological knowledge transfer. The above mentioned studies made reference to convergence and catch-up growth, without imposing conceptual distinction. However, some of the factors discussed, such as spatial interaction and agglomeration are likely to affect growth due to technology transfer. Moreover, initial productivity levels can indicate both a potential for further capital intensity accumulation (convergence) and the potential for technology transfer (catch-up).

The studies below focus on innovation and technology transfer rather than convergence, in their interpretation and empirical analysis of growth performance across European regions. Some of these studies also use per capita income as productivity measure and proxy for technological distance to the frontier. Other studies choose to analyse a more directly technology related measure of productivity, total factor productivity (*TFP*). The studies elaborate empirically on R&D, human capital, trade and technological catch-up as potential growth determinants. Also, some more specific attention is paid to the effect of agglomeration externalities. The empirical analysis in the present paper is closely related to the topic of technology transfer and the framework of catch-up growth underlying these studies.

Crescenzi (2005) investigates regional productivity growth in a cross-section of European regions over the period 1995-2003. Productivity is proxied by GDP per capita at regional level. The empirical specification is an extension of the Fagerberg (1988) model of knowledge transfer, innovation and technological capability. The distance to the technology frontier is proxied by the log of initial GDP per capita level. This reflects the choice for a logarithmic transformation of the relative productivity gap. Productivity growth within regional innovation systems is seen as the result of direct effects and interaction effects between regional innovative activity (measured by composite indicator of R&D and patents) and both human capital and geographical accessibility, which indicate absorption capacity of innovations. The main result is that innovative activities (R&D) are important for growth, but that their effectiveness depends on education levels and accessibility. Furthermore, initial productivity has a negative effect on subsequent growth, which is seen as evidence that catch-up by technology transfer slows down as productivity increases. The study deals with spatial interdependence of growth by expressing variables relative to country means, effectively controlling for country-specific effects.

Sterlacchini (2008) estimates a cross-section growth equation at the regional level for 1995-2002, and shows that the effect of human capital (educational attainment) and R&D on GDP per capita growth differs across regions. Though they are effective (and significant) determinants of growth for richer and/or Northern European regions, these variables lack clear direct effects on growth in less developed and/or more Southern European regions. The specification includes initial per capita GDP as a proxy for the importance of knowledge spillovers as a source of growth, and estimation supports a general catch-up or convergence effect on income growth. Since the variables are expressed as deviations from country means, this implies intra-country catch-up between regions. The study does not venture explicitly into the analysis of interaction terms that may shape the impacts of R&D intensity or distance to the technology leader on growth.

Marrocu et al. (2010) investigate whether regional *TFP* growth in Europe depends on agglomeration externalities. New economic geography theories describe the dynamics of agglomeration, which affects productivity via forward and backward linkages. Recently, the productivity effects of agglomeration have been cast in an endogenous growth framework (Baldwin and Martin, 2004). Changes in urbanization of regions and localization of industries may be important for regional growth in the context of European integration (see Niebuhr and Schlitte, 2004). The analysis focuses on the effects of local agglomeration externalities on growth performance of industries, and pays explicit attention to spatial spillovers (cross-border externalities) using a spatial error model.

The benchmark specifications in Marrocu et al. (2010) assume parameter homogeneity for all variables, and include sector dummies to capture heterogeneity in growth across sectors. Interaction terms with sector- and regional grouping dummies are introduced in an extension to allow for different effects of agglomeration variables across types of sectors and regions. The paper does not focus on technology transfer via catch-up potential and absorptive capacity does not have focus, though initial TFP levels are controlled for. The impact of region-specific variables such as human capital and knowledge capital (e.g., R&D intensity) is controlled for, assuming that these variables affect all sectors similarly. Regional endowments of human capital and technological capital positively relate to growth. The estimation of spatial error models shows the presence of positive spatial autocorrelation, which indicates the presence of spatial heterogeneity (clustering) of growth performance.

Their key results identify differences in importance and effect of specialization (localization) versus diversity (urbanisation) externalities across two broad sectors (low-tech manufacturing and knowledge intensive services) compared to the rest of the economy, and across stage of development (mature incumbent EU economies versus new member states). This suggests a role for interacting specialization and the technology gap, which has not been pursued due to multicollinearity.

Our analysis is similar in nature to the empirical investigation of regional TFP growth in UK industries by Cameron et al. (2005). They explicitly distinguish between direct effects (innovation effects) and effects operating via technology transfer. Their benchmark results assume parameter homogeneity over industries, except for intercept differences. As such, they aim to identify average effects on growth across industry-year observations – instead of sector-specific parameters –, similarly to Marrocu et al. (2010). The study shows that technology transfer is an important explanatory factor for growth across the UK. Second, R&D has a direct positive effect on growth, interpreted as raising the rate of innovation. Third, trade raises productivity growth through technology transfer only, which provides further support for the importance of spatial interaction for productivity growth. Interestingly, human capital effects on productivity growth operate through direct private returns (wages): all effects are captured as direct input enhancement effects. There is no support for external effects (operating through *TFP*). However, much of this result may be related to the fact that *TFP* was calculated controlling for differences in human capital (by using quality-adjusted labour input in growth accounting). These main results suggest that trade is more important for technology transfer than absorptive capacity (R&D or human capital).

The present study contributes to this literature by a shift in focus to the combined effect of innovative activity, human capital and technology transfer. Special attention is paid to the interaction between absorptive capacity and distance to the technological leader in determining the effect of knowledge spillovers on *TFP* growth. This constitutes an additional angle of investigating regional variation in growth performance in the EU, compared to Sterlacchini (2008), Crescenzi (2005) and Marrocu et al. (2010). Furthermore, we allow for parameter heterogeneity in the growth effects of human capital and R&D across three broad sectors and the aggregate regional economy, supplementing the approach applied by Cameron et al. (2005) for the UK.

3. Model specification and data description

Our analysis intends to extend the literature on regional growth by investigating the interactions between knowledge transfer and absorptive capacity at the aggregate and sectoral levels. How does the effectiveness of catch-up growth via technology transfer between EU regions depend on absorptive capacity of regions, as measured by human capital and R&D?

The empirical analysis is related to the approach of Cameron et al. (2005) for UK regions, but based on the logistic model of technology diffusion suggested by Benhabib and Spiegel (2005) instead of a logarithmic transformation of the confined exponential specification introduced by Nelson and Phelps (see Benhabib and Spiegel, 2005). We apply the framework to growth across regions in the EU, and estimate it for both the aggregate economy and three main economic sectors (agriculture, manufacturing and services).

This section first presents the theoretical framework in more detail. Subsequently, we discuss the data used in the analysis. As a prelude to regression analysis, we provide descriptive statistics on convergence in terms of income levels and catch-up in terms of *TFP*. En passant, we show that both measures of productivity are highly correlated in our sample, suggesting how convergence and catch-up perspectives of economic growth are highly intertwined in practice.

3.1. Theoretical framework

Models of catch-up growth 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). Relative productivity levels are interdependent across regions due to spillovers of technological knowledge. In this framework, productivity growth is generated through innovative activity (R&D) and catching-up due to spillovers and adoption of technological knowledge. The technological leader grows at a rate determined solely by its pace of innovation, whereas growth in follower regions benefits from the technological gap to the leader as well as their own innovative activity.

The channel of technology transfer could be knowledge spillovers from international trade or foreign direct investment. In most basic models, the spillover channel is not explicit. These models focus on the importance of the domestic capacity to absorb and adapt foreign knowledge in order to effectuate the transfer of knowledge. Variables that are important for knowledge absorption are the level of human capital present in the region and the intensity of expenditures on research and development.

We follow the logistic growth equation that has been empirically tested for cross-country TFP growth patterns, and preferred within a more general class of models, by Benhabib and Spiegel (2005):

$$\left(g_{TFP}\right)_i = \alpha + \beta \cdot H_i + \gamma \cdot H_i \cdot \left(1 - \frac{TFP_i}{TFP^*}\right) = \alpha + \left(\beta + \gamma\right) \cdot H_i - \gamma \cdot \left(H_i \cdot \frac{TFP_i}{TFP^*}\right) \tag{1}$$

The growth in total factor productivity (g_{TFP}) depends directly on human capital (H) – and potentially other explanatory variables – and on technology transfer. Knowledge spillovers are generated by absorbing knowledge generated at the technological frontier. The knowledge gap is represented by the relative level of *TFP* compared to the technology leader (reflected by an asterix). Adopting existing knowledge is subject to frictions and suffers from diminishing marginal returns as the knowledge gap closes. Benhabib and Spiegel (2005) model the capacity to benefit from the gap as a function of human capital, but could include more variables. Their empirical results show the relevance of the technology gap and of the interaction with human capital in explaining cross-country *TFP* growth performance.

Applying the logistic growth model to regional *TFP* growth in Europe leads to the following general specification used in the present paper:

$$T\hat{F}P_{r,s} = a_r + b_r\left(1 - \frac{TFP_{r,s}}{TFP^*_{r,s}}\right) \qquad (2)$$

The first part on the RHS of the equation states that productivity growth of sector *s* in region *r* depends on a region-specific term a_r (possibly a function of, e.g., human capital and R&D intensity). The second part states that growth depends on the *TFP* level relative to the frontier for region *r* in sector *s* (indicated by an asterix, where $TFP^*_{r,s} \geq TFP_{r,s}$). This captures the regions' potential for technology transfer as the distance to the frontier $\left(1 - \frac{TFP_r}{TFP^*_r}\right)$, and its absorptive capacity, reflected by the term b_r (again, possibly a function of human capital or R&D intensity).

The higher are technological distance and absorptive capacity, the more potential exists for catch-up growth through technology transfer. Provided that the rate of innovation and absorptive capacity settle at stable levels, long-run growth rates of *TFP* will equalize across regions. These properties imply that we can classify the logistic growth model as a semi-endogenous growth model. The region that features the highest rate of innovation will become the technology leader in the long-run. Regional productivity relative to the frontier is endogenous, and converges to region-specific values in the long-run.[2] A region with a lower level of growth-generating

[2] The dynamics of catch-up imply that relative productivity levels will be constant in the long-run. As a result, growth rates will converge and be equal across regions in the long-run. The level of long-run relative productivity is endogenous and derived as follows. The steady state is characterized by equality of *TFP* growth rates:

$$T\hat{F}P^*_r = T\widehat{FP}_r = g_{TFP}$$

This implies that relative productivity of region r, will ultimately be equal to:

$$\frac{TFP_r}{TFP^*} = \min\left[\frac{a_r + b - g_{TFP}}{b};1\right]$$

capacity stabilizes at a lower relative productivity level. At this relative productivity, lower growth-generating capacity is compensated by a higher rate of knowledge spillovers.[3]

Despite absolute convergence of growth rates, the level of this long-run growth, the relative productivity levels when reaching the steady-state growth path, as well as the speed of convergence to this long-run growth path may all be endogenously determined as a function of initial relative productivity, educational attainment and R&D intensity.

The logistic model is realistic in that it maintains the long-run stability properties of neo-classical growth theory. These characteristics are to a large extent consistent with well-established empirical stylized facts on growth and productivity. The framework is flexible, though, in the sense that many insights generated in the endogenous growth literature and from econometric studies on growth determinants can easily be accommodated into the model.

3.2. Data sources and description of variables

The most important elements to model semi-endogenous growth are technological knowledge (proxied by *TFP*), R&D stocks, human capital stocks, and investments in education and R&D by households, firms and the government. All the relevant data series were extracted from Cambridge Econometrics database or EuroStat. The data is collected for NUTS2 regions within EU-27.

Labour productivity is defined as production value per worker. Estimates of *TFP* by region and sector are derived using the approach of growth accounting. This requires region- and sector-specific data on value of production (i.e., gross value added, *GVA*) and factors of production,

[3] In some models, divergence of productivity levels can occur if the potential for knowledge absorption is too low to realize sufficiently high technology transfer to compensate for a lack of innovation. Absorption depends on factors like human capital and R&D. Depending on the functional form of technology transfer and absorption, convergence to stable long-run relative productivity strictly results, or divergence is possible over some range (see Benhabib and Spiegel, 2005).

e.g., labor, (*L*) and capital (*K*). We make use of the Cambridge Econometrics (CE) database for this purpose, summer 2010 edition. The Cambridge Econometrics database contains annual (1980-2012) NUTS2- and NUTS3-level statistics and forecasts of Europe. We make use of the data at the regional level on *GVA*, capital stocks and employment by sector[4]. *GVA* and employment are available for 6 sectors and are broadly grouped into three sectors for capital stocks[5]. We use these three main economic sectors in the empirical analysis:

1. Agriculture, Forestry and Fishing;
2. Manufacturing:
   2.1. Energy and Manufacturing;
   2.2. Construction;
3. Service:
   3.1. Distribution, Hotel & Restaurants, Transport, Storage and Communications;
   3.2. Financial Intermediation, Real Estate, Renting and Business Activities;
   3.3. Non-Market Services.

In order to construct estimates of *TFP* we also need factor (capital and labor) compensation shares in gross value added. To ensure comparability of *TFP* levels the same shares for all regions need to be applied. For information, we have used the EU KLEMS dataset, which contains data on labor and capital compensation on country level. The data used to calculate average factor compensation shares across Europe. The following values were used in the model:

[4] The main source of the CE database is EuroStat's regional branch accounts which are based on the European System of National and Regional Accounts 1995 (ESA95).
[5] Information is available from 1980 onwards for countries from EU-15 and from 1990 for all countries, including Eastern European countries.

Table 1. Compensation share in Cobb-Douglas production function

	Labor share	Capital share
Total economy	0.65	0.35
Agriculture	0.66	0.34
Manufacturing	0.64	0.36
Services	0.66	0.34

The second step in the estimation of *TFP* growth equations requires data on the explanatory variables. In particular, data are needed for human capital and research and development (*R&D*). Unfortunately, data on both explanatory variables are available only on region-specific dimension, but not on sector-specific.

As a proxy for human capital measure we calculated average number of years of schooling in the region. Data on economically active population split by the highest level of education attained is available through EuroStat from 1999 onwards. Average years of schooling were computed with the assumption that to obtain primary education (isced 0-2) one takes 6 years on average, secondary education (isced 3-4) – 10 years, tertiary education (isced 5-6) – 14 years.

As for *R&D* indicator, we consider relative indicators in order to avoid biases due to scale effects. Specifically, we consider *R&D* expenditure as a per cent of *GVA* on regional level. These can be extracted from the EuroStat database. *R&D* expenditure data are not available consistently over time. In the *TFP* equation we use *R&D* intensity only for the year 1997. In the originally available dataset nearly 20% of the data are missing. If data on years 1996 and 1998 are available, we use average of corresponding years to fill gaps (de41, de42). If data at the NUTS 1 level are available, NUTS 2 data available at later years are used to construct shares across NUTS 2 regions used to distribute the NUTS 1 data (itd1, itd2 and 36 NUTS 2 UK regions).

3.3. Descriptive statistics

The figures and tables below present some descriptive statistics for estimated *TFP*, and labor productivity. In Figure 1, the initial aggregate level of TFP in 1997 is plotted against productivity growth over the period 1997-2008 for the European regions in our data set.

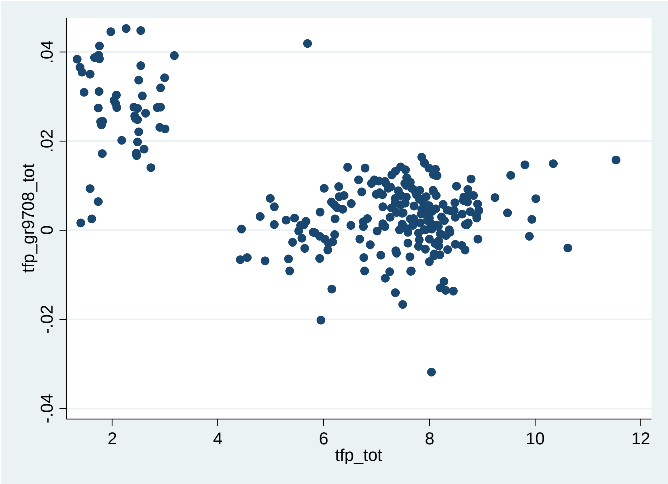


Figure 1. Aggregate *TFP* growth (1997-2008) against its initial level.

It appears that *TFP* growth is higher if the initial level of *TFP* is lower. The regions are clustering into two groups: with relatively low initial *TFP* level and relatively high subsequent growth rates – a group in upper left part of the graph (includes Bulgaria, Czech Republic, Hungary, Poland, Romania and Slovakia); and with relatively high initial productivity and moderate growth rates. The outlier in the upper middle part of the graph is the capital region of Greece (gr30).

The pattern presented in Figure 1 is in line with the concepts of convergence and catch-up presented in the theoretical framework. The fact that *TFP* growth was negative for a significant number of regions could be a result of overestimation of growths in regional employment volume or capital stock (e.g., due to an underestimation of price developments of capital goods).

The question is whether *TFP* estimates are asymmetrically affected, such that regression results of slope coefficients are affected too. A first check is to compare growth rates of *TFP* and labor productivity over the same period. Figure 2 shows that the measures are highly correlated for the aggregate regional economy, and lesser number of regions exhibit negative growth of labor productivity. Therefore it would be consistent to assume that *TFP* estimates were affected symmetrically over the regions and only estimates of intercept in *TFP* growth model would be affected.

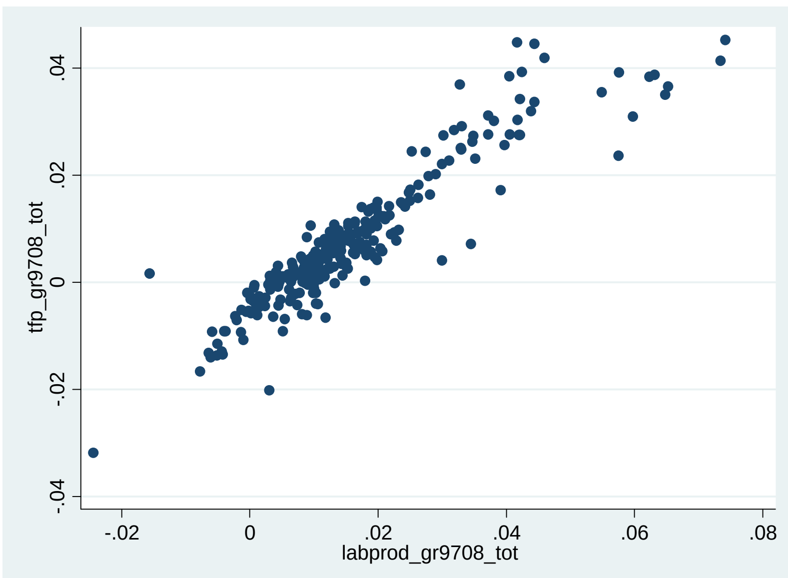


Figure 2. *TFP* growth and labor productivity growth.

In Table 2, selected calculated descriptive statistics are presented. The highest growth of total factor productivity is observed in manufacturing sectors: 1.28% annual average. Growth in agriculture was approximately half as high, but – on the other hand – more than twice as big as in services. It is apparent that growth of productivity in agriculture, as well as initial level of productivity, is relatively dispersed over the regions. Productivity of the economy as a whole differs less across the regions, compared to the three specified sectors. Recall that we have only region-specific data on human capital and *R&D* investment. Assuming that inter-regional discrepancies increase more if we perform the analysis at a more detailed sectoral specification, this implies that availability of sector-specific determinants of productivity growth is becoming more crucial.

Table 2. Descriptives of annualized TFP growth rates, TFP gap and correlation with other variables.

	Average growth (in %)	Minimum growth (in %)	Maximum growth (in %)	Average gap	Correlation of *TFP* growth rates with:			
					Labour prod. growth	Initial level	Human capital	*R&D* intensity
Total economy	0.74	-3.19 (gr24)	4.52 (ro32)	0.45	0.92***	-0.64***	0.41***	0.19***
Agriculture	0.73	-9.08 (uki2)	11.42 (hu33)	0.71	0.93***	-0.41***	0.16**	-0.06
Manufacturing	1.28	-3.42 (itf5)	6.40 (sk02)	0.57	0.87***	-0.50***	0.25***	0.09
Services	0.29	-6.60 (gr24)	4.53 (gr30)	0.46	0.89***	-0.44***	0.53***	0.30***

As indicated in Figure 2, *TFP* growth is highly correlated with labour productivity growth for the whole economy, the correlation coefficients in Table 2 confirm the result for different sectors as well. Productivity growths are significantly correlated with initial levels of *TFP* and log of human capital, although it is much harder to detect significant correlation with intensity of *R&D* investments. Considering correlation values is only a starting point of dependence analysis, more conclusions should be drawn from multivariate regressions in Section 4.

3.4. Empirical specification

To model the growth of productivity (either labour of *TFP*), parameters for the relation between productivity and its explanatory variables need to be estimated empirically. The equation gets the form:

$$\left(g_{TFP}\right)_{r,s} = \alpha_s + \beta_s \cdot LnH_r + \gamma_s \cdot RD_r + \delta_s \cdot LnH_r \cdot \left(\frac{TFP_{r,s}}{TFP^{*}_{r,s}}\right) + \varepsilon_{r,s}\,, \qquad (3)$$

The last term of the above equation represents technology transfer comprising of technological distance and absorptive capacity. This term indicates that, in addition to its importance for innovative capacity, improvement in human capital enhances the closing of the technology gap between the technology leader and the followers. Higher levels of human capital are associated with a faster catching-up process, *viz.* a higher growth of productivity.

4. Empirical results

4.1. Regression results

In this section, we discuss the OLS estimation results of equation (3) for a number of specifications. In Table 3 the results for total factor productivity growth over the total economy and three broad sectors (agriculture, manufacturing, services) are presented. Table 4 presents results of the same specifications for labor productivity growth, as a robustness check. Results are very similar for both types of productivity, so we are focusing on interpretation of *TFP* specifications.

Explanatory power of the specification in equation (3) is the highest for the total economy. This could be a result of limitation on availability of sector-specific explanatory variables. The results show that both human capital and *R&D* investments are positive and significant determinants of productivity growth. Regarding sector-specific results, effect of regional *R&D* turned out to be insignificant in explaining productivity growth in agriculture and thus the explanatory variable was omitted from the estimation equation for the specific sector. In other sectors, *R&D* is significant at 10% level. Human capital and its interaction term with relative initial productivity that shows catch-up effects are both significant at the 1% level. The negative coefficient for the interaction term confirms the spillover hypothesis, and indicates that effects of human capital are higher in the regions lagging behind in terms of technological development (in line with Benhabib and Spiegel, 2005). It should be again noted that both *R&D* and human capital measures are available only on the regional level and thus the impact on specific sectors is a combination of direct and inter-sector spillovers effects.

In order to interpret the contribution of different variables to the explanation of variation in *TFP* growth rates, Table 5 presents standardized regression coefficients (beta coefficients). These translate the estimated regression parameters to the relative average contribution of the independent variables to the explanation of average variation in *TFP* growth rates in the sample. It appears that variation in human capital has a greater effect on *TFP* growth differences across regions than *R&D* intensity. Standardized coefficients of catch-up term should be interpreted with caution. Their relatively high absolute values reflect the average effect on *TFP* growth of one standard deviation increase, but this implies an increase in both human capital and technological gap measure nearly by one corresponding standard deviation. The most significant effect of human capital is observed in services, a change of one standard deviation results in change of *TFP* growth by nearly 43% of its standard deviation if we take into account that average *TFP* gap in services equals 0.58. Effects of *R&D* in manufacturing and services are very close, implying correspondingly 11% and 10% response of productivity growth.

Table 3. Total factor productivity regression results

Sector	*Intercept*		*lnH*		*R&D*		*lnH*GAP*		R^2
	Coeff.	St.Err	Coeff.	St.Err	Coeff.	St.Err	Coeff.	St.Err	
Total	-0.1450***	0.0122	0.0760***	0.0057	0.0917**	0.0431	-0.0167***	0.0016	0.56
Agriculture	-0.1244***	0.0439	0.0708***	0.0196	-	-	-0.0309***	0.0038	0.24
Manufacturing	-0.1585***	0.0275	0.0844***	0.0131	0.1312*	0.0752	-0.0226***	0.0044	0.27
Services	-0.1420***	0.0165	0.0682***	0.0077	0.0854*	0.0477	-0.0092***	0.0020	0.40

The dependent variable in the regressions is an average annual growth rate of TFP over 1997-2008. R&D is a per cent of R&D expenditures in gross value added in 1997, H is a human capital measure as described above in 1999. Regressions are performed using OLS with robust errors.

*** - significant at 0.1; ** - significant at 0.05; * - significant at 0.01.

Table 4. Labour productivity regression results

Sector	*Intercept*		*lnH*		*R&D*		*lnH*GAP*		R^2
	Coeff.	St.Err	Coeff.	St.Err	Coeff.	St.Err	Coeff.	St.Err	
Total	-0.1197***	0.0135	0.0656***	0.0062	0.1317***	0.0490	-0.0161***	0.0020	0.47
Agriculture	-0.1136**	0.0520	0.0708***	0.0237	-	-	-0.0325***	0.0069	0.15
Manufacturing	-0.2004***	0.0327	0.1035***	0.0155	0.2034**	0.0832	-0.0206***	0.0067	0.31
Services	-0.1055***	0.0178	0.0528***	0.0081	0.1075*	0.0550	-0.0077***	0.0022	0.30

The dependent variable in the regressions is an average annual growth rate of labour productivity over 1997-2008. R&D is a per cent of R&D expenditures in gross value added in 1997, H is a human capital measure as described above in 1999. Regressions are performed using OLS with robust errors.

*** - significant at 0.1; ** - significant at 0.05; * - significant at 0.01.

Table 5. Standardized beta coefficients, *TFP* growth regressions

Sector	*lnH*	*R&D*	*lnH*GAP*
Total economy	0.7151	0.1187	-0.6165
Agriculture	0.2079	-	-0.4634
Manufacturing	0.5083	0.1087	-0.5435
Services	0.5937	0.1023	-0.2764

To summarize, all the sectors are apparently characterized by higher effect of human capital level and technology adoption. Service sector benefits the most from human capital accumulation. On the other hand, effect of technological adoption from technological leader is the highest in manufacturing sector.

4.2. Simulation of growth impacts: shocks to human capital and R&D

In this section, we apply the regression results to illustrate the impact occurring in the different sectors if we shock the economy of an average region with an increase in human capital and *R&D* investments. This serves to show the economic impact of a set of potential policy interventions, and the steady-state long run properties of the model, as argued in Section 3.1. Estimated coefficients are taken from Table 3. Characteristics of the leading region, which are Övre Norrland in case of agriculture, Groningen – manufacturing, and Inner London – services, and of an average region are presented in Table 6.

Table 6. Characteristics of the regions used in simulation exercise.

Sector	*lnH*	*R&D*	*TFP*		
			Agriculture	Manufacturing	Services
Leading region	2.4471	0.0132	17.9527	26.6108	14.6637
Average region	2.3019	0.0163	4.9617	8.4910	6.8005

The shock applied to human capital in the average region is a permanent 1% increase, the shock applied to *R&D* expenditure is a 10% increase. Following figures show changes in cumulative *TFP* growth due to proposed shocks to human capital and *R&D* investments compared to benchmark *TFP* growth paths. The increase in *TFP* levels relative to the benchmark growth path stabilizes over time, for agriculture and manufacturing somewhat faster than for services. There are two sources of increased productivity growth: via the direct effect of increased human capital stock (and *R&D*) and via increased absorptive capacity of the region.

Half-life of transition to a new steady state growth path takes around 20 years for agriculture and manufacturing sector and nearly 50 years for service sector. Beside, one can observe that firstly productivity growth accelerates relative to the benchmark. But then, for two out of three sectors, it becomes slower than in the benchmark and only after the slowdown finally stabilizes. The dynamics could be explained by too abrupt initial take off in agriculture and manufacturing which led to substantial decrease in the *TFP* gap relative to the benchmark. Higher level of human capital was not enough to compensate rapidly closing gap and slowdown in growths occurred. Long-run productivity effects of the simulated permanent shocks to human capital and *R&D* are around 0.65% in agriculture, 2% in manufacturing, and 6% in services (compared to the benchmarks).

It should be noted that these shocks only serve illustrative purposes; no attention is paid to the relation to actual policy processes. Moreover, the simulated long-run effects and transition paths depend on the simulation set up. In this case, we for example assumed that variables of the leader are fixed over time. But these details don’t change the general conclusion that a permanent increase in a factor determining *TFP* growth results in a stable increase in productivity in the long run.

Figure 3. Relative TFP effect in agriculture of 1% shock to human capital and 10% shock to R&D investments compared to benchmark with no shocks.

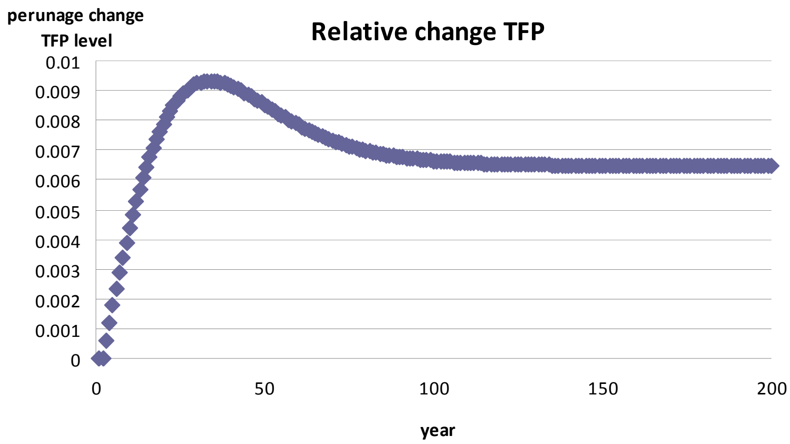


Figure 4. Relative TFP effect in manufacturing of 1% shock to human capital and 10% shock to R&D investments compared to benchmark with no shocks.

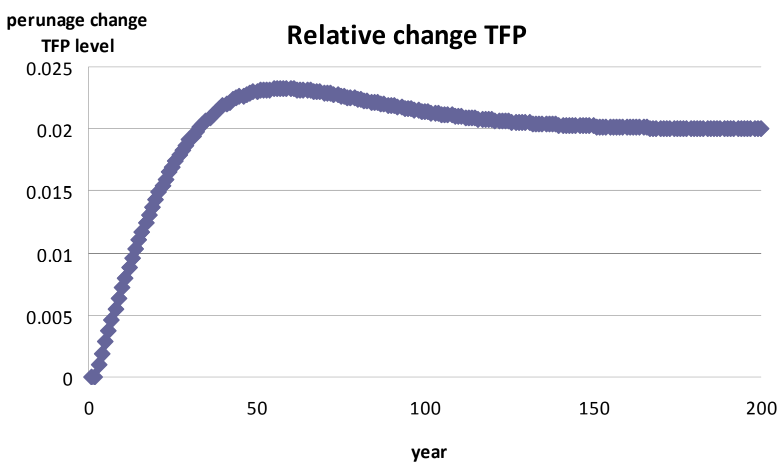
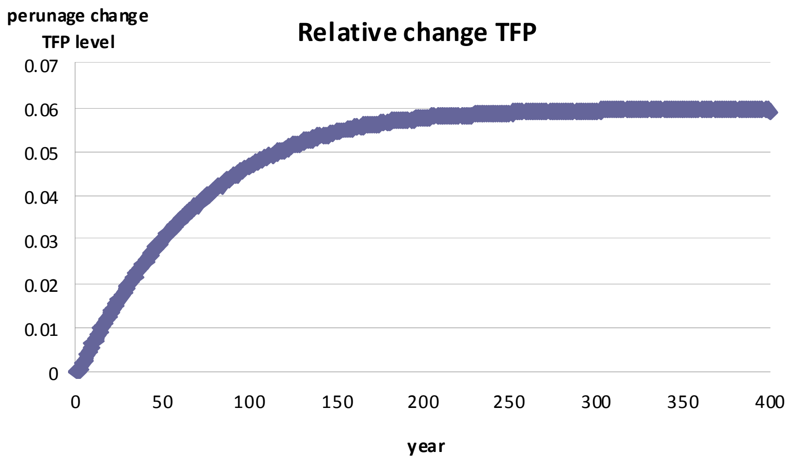


Figure 5. Relative TFP effect in services of 1% shock to human capital and 10% shock to R&D investments compared to benchmark with no shocks.



5. Conclusion

One of the big challenges for the European Union and its member states is to decrease regional income disparities without hampering economic growth processes. For long term income prospects, productivity growth is essential and innovation is seen as a crucial factor for sustained productivity growth. To increase cohesion between regions, convergence in incomes is important. Fostering technology transfer is essential for regions and countries to catch up to the productivity levels in the leading territories. Though potential for knowledge spillovers is higher if regions are farther behind in terms of technological knowledge, this may not be enough to guarantee fast catch-up. Educational attainment of the workforce and R&D expenditure are thought of as important determinants of both innovative activity and knowledge spillovers. Both are subject to government policy intervention. For this reason, it is important to understand the impact of these variables on productivity growth and technology transfer.

This paper has presented an empirical analysis of regional (total factor-) productivity growth across Europe at the aggregate level and for the three main economic sectors. The main contribution of the analysis is the explicit attention to the interplay of initial productivity distance to the frontier, absorptive capacity and innovative activity within a clear theoretical framework, and its application at the regional level for the EU. Due to data limitations (R&D expenditures and human capital indicators were only available at the regional level), some of the results for individual sectors need to be interpreted cautiously.

Our empirical results show that human capital is both important as a direct determinant of total factor productivity growth, and in facilitating technology transfer. Complementing earlier studies, we find empirical support for the theoretical hypothesis that the potential for catch-up growth is higher for regions with a lower initial relative productivity, conditional on the availability of sufficient human capital. Regional R&D investment intensity is found to be of importance as a direct determinant of regional productivity growth, but not for growth in agriculture – perhaps because total regional R&D expenditure may not correlate highly enough with unobserved R&D at the sectoral level. Consistent evidence for catch-up growth was found. The further away a region initially is to the productivity leader, the higher its subsequent growth was estimated to be, all else equal.

For future research, we can identify a number of relevant extensions. The literature has shown the importance of the spatial dimension in explaining regional growth. Spillovers occur over space and may be conditioned by location, proximity and spatial interaction. Several options are available to take this dimension into account. First, controlling for country-specific effects may control for part of spatial heterogeneity (or clustering) in growth performance. However, at the intranational level, divergence patterns may exist, for example due to agglomeration forces. This may affect the catch-up evidence found in this study, which occurs relative to the European technology leader. Second, it entails specific attention for the role of spatial accessibility, distance and spatial interaction in the specification of the relevant technology gap. Estimation that accounts for spatial dependence (spatial lag structures) and spatial heterogeneity (spatial error models) is a useful approach for taking the role of space into account (e.g., see Abreu et al., 2004), especially since data availability on interregional spatial interaction prove notoriously problematic.

A further extension is to account for intersectoral spillovers. For this, rethinking the specification choice of the total factor productivity growth equation is needed. One approach, along the lines of Marrocu et al. (2010), is to further test the role and importance of agglomeration externalities for catching-up and for innovative activity. Also, the relevant technology gap may be conditioned by production structure to reflect intersectoral spillovers.

During the process of extending the empirical specification, it is necessary though to keep in mind the importance of interpreting the effects in terms of economic transmission channels and economic significance within a clear theoretical framework.

List of relevant literature

Abreu, M., H.L.F. de Groot, and R.J.G.M. Florax (2004): *Spatial Patterns of Technology Diffusion: An Empirical Analysis Using TFP,* unpublished manuscript.

Baldwin, R.E. and P. Martin (2004): Agglomeration and regional growth, in: V. Henderson and J.F. Thisse (eds.), *Handbook of Regional and Urban Economics: Cities and Geography*, Amsterdam: Elsevier.

Barro, R. (1991): Economic Growth in a Cross Section of Countries, *The Quarterly Journal of Economics*, 106(2), pp. 407-443.

Barro, R. and X. Sala-i-Martin (1995): *Economic Growth*, New York: McGraw Hill.

Barro, R. and X. Sala-i-Martin (1997): Technological diffusion, convergence and growth, *Journal of Economic Growth*, 2 (1), pp. 1–26.

Barro, R., X. Sala-i-Martin, O.J. Blanchard and R. Hall (1991): Convergence Across States and Regions, *Brookings Papers on Economic Activity*, 1991(1), pp. 107-182.

Baumol, W. (1986): Productivity Growth, Convergence and Welfare: What the Long-Run Data Show, *The American Economic Review*, 76 (5), pp. 1072-1085.

Benhabib, J. and M.M. Spiegel (2005): Human Capital and Technology Diffusion, in: P. Aghion and S.N. Durlauf (eds.), *Handbook of Economic Growth, Volume 1A*, pp. 935–966.

Bräuninger, M. and A. Niebuhr (2005): Agglomeration, Spatial Interaction and Convergence in the EU, *HWWA Discussion paper*, No. 322 Hamburg Institute of International Economics.

Cameron, G., J. Proudman and S. Redding (2005): Technological convergence, R&D, trade and productivity growth, *European Economic Review*, 49, pp. 775–807.

Crescenzi, R. (2005): Innovation and Regional Growth in the Enlarged Europe: The Role of Local Innovative Capabilities, Peripherality, and Education, *Growth and Change*, 36 (4), pp. 471–507.

Fagerberg, J. (1988): Why growth rates differ, in: G. Dosi, C. Freeman, R. Nelson, G. Silverberg, and L. Soete (eds.), *Technological change and economic theory*, pp. 432–457, London: Pinter Publishers.

Howitt, P. (2000): Endogenous Growth and Cross-Country Income Differences, *American Economic Review*, 90 (4), pp. 829–846.

Keller, W. (2004): International Technology Diffusion, *Journal of Economic Literature*, 42 (3), pp. 752–782.

Marrocu, E., R. Paci and S. Usai (2010): Productivity Growth in the Old and New Europe: The Role of Agglomeration Externalities, *CRENOS Working Papers*, No. 2010/24, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

Niebuhr, A. and F. Schlitte (2004): Convergence, Trade and Factor Mobility in the European Union – Implications for Enlargement and Regional Policy, *Intereconomics: Review of European Economic Policy*, 39 (3), pp. 167–176.

Prescott, E.C. (1998): Lawrence R. Klein Lecture 1997: Needed: A Theory of Total Factor Productivity, *International Economic Review*, 39 (3), pp. 525–551.

Romer, P.M. (1994): The Origins of Endogenous Growth, *Journal of Economic Perspectives*, 8 (1), pp. 3–22.

Romer, P.M. (2010): Which Parts of Globalization Matter for Catch-Up Growth?, *NBER Working Paper Series*, No. 15755, National Bureau of Economic Research, Cambridge MA.

Sterlacchini, A. (2008): R&D, higher education and regional growth: Uneven linkages among European regions, *Research Policy*, 37, pp. 1096–1107.

Tselios, V. (2009): Growth and Convergence in Income Per Capita and Income Inequality in the Regions of the EU, *Spatial Economic Analysis*, 4 (3), pp. 343–370.