Education or Creativity:
what matters most for economic performance?

Emanuela Marrocu and Raffaele Paci
University of Cagliari, CRENoS

Abstract

There is a large consensus among social researchers on the positive role played by human capital on economic performances. The standard way to measure the human capital endowment is to consider the educational attainments by the resident population, usually the share of people with a university degree. Recently, Florida (2002) suggested a different measure of human capital - the "creative class" - based on the actual occupations of individuals in specific jobs like science, engineering, arts, culture, entertainment. However, the empirical analyses carried out so far overlooked a serious measurement problem concerning the clear definition of the education and creativity components of human capital. This paper aims to disentangle this issue by proposing a disaggregation of human capital into three non-overlapping categories of creative graduates, bohemians and non creative graduates. Using a spatial error model to account for spatial dependence, we assess the concurrent effect of the human capital indicators on total factor productivity for 257 regions of EU27. Our results indicate that the highly educated creative group is the most relevant one in explaining production efficiency, non creative graduates exhibit a lower impact, while the bohemians do not show a significant impact on regional performance. Moreover, a relevant influence is exerted by technological capital, cultural diversity and industrial and geographical characteristics thus providing robust evidence that a highly educated, innovative, open and culturally diverse environment is becoming more and more central for productivity enhancements.

Keywords: human capital, creativity, education, TFP, technological capital, diversity, European regions
JEL code: R10, J24, O30

Acknowledgments: The research leading to these results has received funding from the ESPON project KIT, Knowledge, Innovation, Territory. We would like to thank Barbara Dettori for her excellent assistance.

June 2011

Working Paper CRENoS 2010/31

1. Introduction

There is a large and long-standing consensus among economists and social scientists on the key role played by human capital in influencing productivity levels and growth (Lucas, 1988). The availability in a specific area of skilled and highly educated people can be seen as the primary determinant of the local economic performance since other important factors, like the creation of new ideas and technological innovations, are strongly reliant on the human capital endowment. Broadly speaking, the idea is that a higher endowment of human capital, skills and creativity in a certain area represents an advantage for the localization of high-performing innovative enterprises, this localisation process is self-reinforcing and therefore firms and local productivity are enhanced (Jacobs, 1969). This virtuous mechanism tends to accentuate the regional polarisation pattern given the existence of localised agglomeration externalities (Krugman, 1991).

One of the key and still open research questions is how to measure the human capital endowment in a specific area. The standard and most used indicator for human capital is educational success, usually measured by the share of population who attained at least a university degree. However, this proxy has been recently criticised on the ground that it is not able to capture the real capabilities of each individual that are based not only on schooling but also on personal skills - like creativity and innovativeness - and on accumulated experience.

In his bestseller book Florida (2002) suggests that what people really do is more important than what is stated in their formal education attainments. More specifically, he proposes to utilize the level of creativity in the local economy, measured by the share of population employed in occupations like sciences, engineering, education, culture, arts and entertainment[1]. Creative people are workers whose economic function is to identify problems and to find out original solutions by creating new ideas and technology or combining existing knowledge in new and innovative ways. The use of the creative class measure would allow one to detect the current occupational clusters at the local level and to analyse their effect on regional performance. After the success of Florida's book the influence of the creative class on urban and regional performances has been tested in several contributions applied to different geographical contexts. The European Commission has declared 2009 as the year of creativity, highlighting its potential impact on regional economic performance (European Commission, 2009).

On the other hand, the view that creativity exerts an independent positive role on local performance has been strongly criticised on the ground that the set of individuals occupied in

[1] The idea that different occupations, even among graduated individuals, affect economic development in a very differentiated way is not new in the literature. For instance Murphy et el. (1991) remarked that countries with a higher proportion of engineers grow faster, whereas countries with a higher proportion of lawyers grow more slowly.

creative jobs strongly overlaps with the number of individuals holding a tertiary degree. In a critical review of Florida's contribution, Glaeser (2005) shows that if an indicator of schooling (population with a bachelor's degree) is added as an explanatory variable of population growth in the USA metropolitan areas, then all the creative variables become irrelevant. This proves that once we control for the traditional measure of human capital – schooling – there is no role left for bohemians and other creative types to explain local economic performance.

Overall, the controversy on how to measure human capital (education or creativity) and which of the two elements plays a major role is still open and the answers require additional empirical research.

It is important to remark that the key issue, often neglected in the literature, is the strong overlapping between graduates and creatives. Most of the individuals included in the creative class (according to Florida's definition) are indeed graduates, so it is very difficult to disentangle which effects on local performances are due to their creativeness or to their education. In the empirical analyses the unclear identification of the education and creativity components generates a measurement problem, leading to confusing evidence as the human capital effects are poorly estimated due to either multicollinearity problems or to omitted variable bias. Therefore, it is necessary to define clearly the various categories of education and creativity in order to attain a more accurate evaluation of their impacts.

The main purpose of this paper is to provide an empirical contribution to the literature by trying to distinguish the various components of human capital. We propose a disaggregation of human capital into three non-overlapping categories of *creative graduates*, *bohemians* and *non creative graduates*. These are identified by combining the information on educational attainments with the one related to the actual occupations in an attempt to simultaneously account for both potential and on-the-job utilized skills.

We assess the concurrent effects of the human capital indicators on the economic efficiency of 257 regions belonging to the 27 countries of the European Union (see Appendix 1 for a list of the regions considered). It is worth emphasising that this is the first time that the concurrent effects of graduates and creatives is analysed for a large and differentiated group of regions, thus providing more general and robust empirical results.

An original aspect of our contribution regards the measurement of the local economic performance, which is another central and controversial point largely debated in the literature. Some studies have employed indirect outcomes like the number of innovations or the presence of high tech industries; other contributions have used final, although quite rough, measures of economic performance as employment. In this paper, as an indicator for regional economic performance, we use an estimated measure of total factor productivity (TFP), which already accounts for the contribution of the traditional production factors (capital and labour). It is, thus, robust to the structural change processes that have been taking place in all European economies over the last decades and that have significantly affected the dynamics of employment growth. This makes the latter variable not adequate as a performance indicator to be used for assessing the role of human capital in determining economic outcomes.

Further, another important element of our analysis is to consider other interrelated features of the local environment, such as the institutional setting, the production of knowledge, cultural diversity and the productive structure, which contribute to drive the success of a regional economy as they are often associated with the presence of high skill people in a specific area (Glaeser et al., 2001; Dettori et al., 2010). The issue of assessing the role of education and creativity once the external institutional and economic environment has been controlled for is particularly important for the European context, which is characterized by a high regional heterogeneity (Asheim and Hansen, 2009). Therefore, we test for the robustness of our results by controlling for several important elements of the regional economy, like the availability of technological capital, the degree of tolerance and cultural diversity, the industrial structure and the regional hierarchy, which are expected to interact with human capital in determining local productivity.

Finally, since our observations refer to geographical regions, in the empirical analysis we adopt the specific estimation approach that allows taking into account the issue of spatial dependence between neighbouring regions.

The paper is organised as follows. In the next section we discuss the various measures of human capital used in the literature and suggest a way of defining three non-overlapping categories. The third section examines other characteristics of the regional environment which affect regional performance. Section 4 presents the estimation of the regional TFP, which is our preferred indicator of economic performance. In section 5 we present the empirical model and discuss some methodological issues. The econometric results for the basic model are presented in section 6 together with some robustness exercises. Section 7 concludes. A complete definition of the variables and data sources is presented in Table A2 in the Appendix.

2. Human capital measures

In this section, after a brief review of the relevant literature, we try to disentangle the issue of measuring human capital endowments by proposing a classification, based on the available measures of occupation and education attainment, which is expected to move in the direction of overcoming the serious measurement problem present in the literature.

Following Florida's contribution the concept, measurement and effects of creativity have obtained great attention (Peck 2005; Villalba 2008). In recent years the influence of the creative class on urban and regional performance has been analysed in several contributions applied to various geographical contexts spanning from the US metropolitan areas (Florida et al. 2008) and rural and urban counties (McGranahan and Wojan, 2007) to Australia (Atkinson and Easthope 2009), to the regions of a single European country, like the UK (Nathan, 2007), Sweden (Mellander and Florida, 2007), the Netherlands (Marlet and van Woerkens, 2007), Germany (Wedemeier, 2010) and to a group of Northern European countries (Boschma and Fritsch, 2009; Andersen et al., 2010).

It is difficult to propose a consistent interpretation of the findings of these studies, given the differences in the institutional settings, econometric methodology, measures of regional performance and included control variables. In some cases the creative class measures outperform the conventional education indicators in accounting for regional development, as in Marlets and Van Woerken (2007) for the Netherlands and Mellander and Florida (2007) for Sweden. Similar result are found by McGranahan and Wojan (2007) using a more restrictive definition of creative occupations; they show that creativity has an effect on employment growth in rural US counties independent of the endowment of graduated people. On the other hand, some studies show that the creative class hypothesis is not supported, as it is the case for the UK city performance (Nathan, 2007). Contrasting results are also found by Boschma and Fritsch (2009): considering both proxies of human capital in a model of employment growth they find that the creative class measures dominate the education indicator in the Netherlands, whereas the opposite happens in Germany. Moreover, in the analysis of four Nordic countries (Denmark, Finland, Norway and Sweden) Andersen et al. (2010) show that the positive role of the creative class in supporting economic development is confirmed only for the case of the large city regions, while results for the smallest areas do not show a similarly strong role. In other studies the two measures of human capital seem to play different but complementary roles. Florida et al. (2008), within a path model of regional development system, show that the creative class influences labour productivity while the educational attainments affect regional income.

In our opinion, the key issue, often overlooked in the literature, is that the significant overlapping between the two measures of human capital – education and creativity – may yield misleading empirical results. Indeed the empirical specifications may suffer from either a multicollinearity problem (if the two components are included together) or from an omitted variable problem (if only one measure in considered). To tackle this problem it is worth starting with a careful reconsideration of the various definitions of creativity.

We begin our analysis by focussing on the classification of the creative individuals initially suggested by Florida and commonly used in the literature; more specifically we follow the classification used by Boschma and Fritsch (2009) which is based on the International Standard Classification of Occupations (ISCO, 88) collected in the European Labour Force Survey[2]. Table 1 shows that the category usually called Creative Class (CC) can be decomposed into two main categories:

A. the *Creative Graduates* (CG), including scientific, life sciences, health, teaching, librarians and social sciences professional occupations (this group corresponds to the one usually refer to as "super creative core" or "creative core" in the existing literature);

B. the *Bohemians* (B), consisting of artistic, entertainment and fashion professionals.

The point we want to stress is that the occupations listed in Table 1.A belong to the "Major group 2, Professionals" of the ISCO classification and require the tertiary level of education. It is obvious that to become, for instance, a physicist, or an architect, or a medical doctor, or even an economist, at least a tertiary degree is required[3]. This is why it is misleading to label this group "creative core", as it is done in the literature, since they are, at the same time, individuals with a *degree* working in *creative* occupations. It is really difficult to claim that the creative aspect is more important than the educational one for the case of, say, a medical doctor or an engineer. Moreover, while the attainment of the degree (and thus the educational component) is an incontrovertible fact, the assessment of the creative content of an occupation is more disputable. Thus, to gain clarity in the interpretation of these occupations and to avoid serious measurement problems in the empirical analysis, we prefer to define group A in Table 1 as *Creative Graduates*.

The second category B is usually labelled as *Bohemians* and it includes several creative occupations like writers, painters, musicians, dancers, actors, designers, acrobats, athletes and many

[2] It goes beyond the scope of our contribution a discussion on which occupations are really creative and if they should be included among the various groups of creatives (for a critical view see Markusen 2006; McGranahan and Wojan, 2007). Our interest is to try to distinguish between the creative and the educational components of human capital, within a widely used classification.

[3] There may be few exceptions: for examples for occupations like Primary education teaching professionals or Archivists it is possible that, in the past, tertiary education was not a formal requirement in some European countries.

others. For this group it is more complicated to discern the individual educational attainment just looking at the occupations list. For instance, most of classical musicians and directors are expected to have a tertiary level of education but, possibly, rock musicians do not have a university degree. Unfortunately, it is not possible to have direct information on the educational attainment of these individuals[4]. Therefore, we make the most unfavourable hypothesis with respect to our purpose of assessing the specific contribution of the creative component on local performance: namely, we assume that all bohemians are just creative and are not graduated. Therefore, we presume that in these occupations the creative components are essential and predominant with respect to the educational one. The idea is that when we read a novel or listen to a concert we care about the talent and creativity of the artist rather than her educational level. We are aware that, with such an hypothesis, we are probably inducing another kind of measurement error, as at least a certain number of bohemians hold a degree and should be added to the creative graduates group. However, in the econometric analysis we will try to control for this possible measurement error showing that the estimation results are not affected.

The other type of data available to measure the regional endowment of human capital is the education attainment. The influence of education has been well documented in nation-wide studies (Mankiw et al., 1992; Benhabib and Spiegel, 1994) and also at the regional level (see, among many others, Rauch, 1993 for US case; Di Liberto, 2008 for Italy; Ramos et al., 2010 on Spain; Fischer et al., 2009a for the European regions). Moreover, this issue is becoming even more relevant since the differences in human capital endowments are increasing at the regional level due to local agglomeration effects (Berry and Glaeser, 2005).

Following a well established literature, we proxy human capital by Graduates (G), i.e. the number of employed people who has attained at least a university degree (ISCED 5-6). For this group of people no detailed information is available on the jobs they are actually employed in. But, as we have already stressed, a relevant part of them are already counted within the Creative Graduates category described above. Thus, it is not correct to include both categories in the econometric analysis since this would not yield reliable estimates of their separate effects because of multicollinearity problems. We need to isolate the group of Creative Graduates from the rest of the population holding a degree; to this aim we introduce a new category:

C. *Non Creative Graduates* (NCG), computed as the difference between the total number of employed graduates and the creative graduates. In Table 1.C we report the most likely

[4] Ideally we would need data disaggregated by 3-digit ISCO occupations, by educational attainment and by NUTS2 regions. However such detailed information are not available even in the micro data due to the anonymisation procedures.

expected occupations of the non creative graduates; they include legislators, government officials, managers, business and legal professionals. This list is not exhaustive since we may have a graduate working as a farmer or as a clerk, but this possibility does not affect our procedure which aim at distinguishing this category from the creative groups[5].

Figure 1 shows the interconnections among the three human capital categories by reporting the European average shares over population. We notice that employed graduates count for the 12.5% of population and among them the non creative graduates are the major component (7.2%), while the creative graduates are equal to 5.3%. On the other hand, the average share of the creative class in Europe is equal to 5.9% of population and the great majority of them are creative graduates (5.3%) while only 0.6% are bohemians[6].

We believe that having identified on the basis of their occupational contents the three non-overlapping groups of non creative graduates, creative graduates and bohemians, makes operational for empirical purposes the distinction between the formal education and the creativity components of human capital.

The spatial distribution of the three measures of human capital in the European territory is shown in Figures 2-4 while the summary statistics are reported in Table 2.

The geographical distribution of the creative graduates is reported in Figure 2, it clearly turns out that the presence of the highly educated and creative people follows a well defined spatial pattern with the highest values recorded for the Scandinavian, Baltic and Northern countries (Germany, United Kingdom and the Netherlands), while the Southern and Eastern countries show a lower presence of creative graduates. Looking at the regional level in more detail, we notice that the creative graduate group is larger, as expected, in the urban regions; indeed in the top positions there are the capital cities (Stockholm, Helsinki, Paris, Bucharest, Prague, Amsterdam) and other regions, close to the capital city, which host universities renowned world-wide (Utrecht, Oxford, Louvain-la-Neuve).

The second component of the human capital endowment is the bohemian group, who represents a small share of the population (0.6% for the European average) since it includes only the strictly creative occupations listed above. The most "bohemian" region is Inner London (4.4% of

[5] Some of these occupations (Major group 1 Legislators, senior officials and managers; business professional, legal professionals) are included in the category "creative professionals" (Florida et al, 2008; Boschma and Fritsch, 2009). Again it is quite disputable if these jobs are indeed creative but, for our goal, the crucial point is that they require a degree. Therefore their inclusion in the creative class will only widen the overlapping between creative and education components introducing an even more severe problem of multicollinearity.

[6] Our figures for the entire Europe are in line with those reported by Boschma and Fritsch (2009) for a subset of Nordic countries.

population) followed by the Amsterdam region (2.7%) and other city regions like Stockholm, Outer London, Hamburg, Praha, Berlin. Indeed the spatial distribution of the bohemians (Figure 3) appears more scattered and this high spatial dispersion is also confirmed by the high value of the coefficient of variation (0.79) compared to the other human capital indicators (see Table 2). A low presence of bohemian occupations is detected in the Southern regions of Portugal, Spain and Italy, but also in France and in several Eastern countries.

Finally we consider the third and largest component (7.2%) of human capital, composed by employed individuals with the tertiary level of education not occupied in creative jobs, whose distribution (Figure 4) shows a strong national pattern. High values can be found for all regions in Spain, France, UK, Germany, the Netherlands and also in the Scandinavian and Baltic countries. On the other hand, low values appear almost uniformly distributed for the other Southern and Eastern countries.

3. Other characteristics of the regional environment

The main interest of the paper is to assess the influence of different measures of human capital on the efficiency levels of the European regions. Nonetheless, it is important to control for other variables which are expected to affect the regional TFP and, at the same time, are strictly related to the presence of high skill people in the area. In particular, in our empirical model we include several additional factors which are perceived as more and more relevant in shaping the local environment: the technological capital, the level of diversity and tolerance, the industrial and geographical characteristics.

The first factor is the technological capital which represents a relevant aspect of the intangible assets essential to enhance the productivity of the local economy. The impact of a direct measure of technological stock on the output level was originally suggested by Griliches (1979) in the so-called knowledge-capital model and afterwards it has been used in several contributions at the enterprise, region and country level. This approach emphasizes the characteristic of public good assumed by technology, so that firms benefit from the availability of technological capital at the local level and, in turn, this enhances the regional performance[7]. Some recent studies (Rodriguez-Pose and Crescenzi, 2008; Sterlacchini, 2008; Fischer et al. 2009b) have examined the effects of technological capital on the European regions performance offering general support to the positive

[7] See the survey by Audretsch and Feldman (2004) on the numerous contributions, based on different theoretical approaches, that have studied the effect of technology on the economic performance.

role exerted by the innovation variables on economic outcomes. In this paper, as an indicator for technological capital, we use the stock of patent granted by EPO in the period 2000-2004 divided by total population. The data have been regionalised on the basis of the inventors' residence; in the case of patents with multiple inventors, proportional quotas have been attributed to each region. The geographical distribution of the technological capital across the European regions is represented in Figure 5. It shows a clear pattern of spatial concentration remarked also by the high value of the coefficient of variation (CV = 1.27) compared to the other variables (see Table 2). The map shows a well defined cluster of high-performance regions which starts in France, passes through the Northern regions of Italy and embraces most German regions. Sweden, Finland and Denmark show top-high innovation performance, signalling the presence of a Scandinavian cluster. On the other hand, all Southern and Eastern European regions are characterised by very low levels of technological capital.

The second variable is the degree of cultural diversity in the region, which is supposed to favour local performance since it signals the regional capacity to attract people from outside. It is not an easy task to find an appropriate measure for a multifaceted factor as diversity and this task is even more difficult since we need to measure it at the regional level for the whole of Europe. Hence, we use the number of people living and working in any one of the 257 European regions, but born in a foreign country, as a proxy of cultural diversity. In general, people born abroad bring diversified backgrounds in the new country of residence[8] and this facilitates the diffusion of new ideas, which, in turn, yields an increase in creativity and productivity for the whole economy[9]. Moreover, migrants are usually younger and therefore more dynamic and open to new ideas and technologies. This measure has been already used by Ottaviano and Peri (2006) for the US cities and by Bellini et al. (2008) for the European regions.

From Table 2 it appears that the average value of foreign born population in Europe is 6.9% and it shows a high variability going from the minimum value of 0.01% in the Romanian region of Centru to the highest value of 37.6% in Inner London. It is interesting to remark that the variability of this indicator across regions (CV = 0.83) is much higher with respect to the human capital measures previously analysed. Figure 6 shows that the highest degree of cultural diversity is found in the capital cities (London, Brussels, Luxembourg, Wien, Paris, Stockholm, Madrid), but also in

[8] "Immigrants have complementary skills to native born not only because they perform different tasks, but also because they bring different skills to the same task" (Florida et al. 2008, p. 620).

[9] For the case of London firms, Nathan and Lee (2011) provide evidence suggesting that firms diverse in terms of ownership, teams or management are more innovative in developing new products and in implementing new processes. They also provide a quite exhaustive description of how the links between cultural diversity and innovativeness work at individual, firm and urban level.

some attractive coastal areas like Isles Baleares, Valencia, Catalonia, Provence, Côte d'Azur. On the other hand, as expected, in most regions of the Eastern countries (Romania, Bulgaria, Hungary and Poland) the share of foreign born population is very low.

Strictly related to cultural diversity is the level of tolerance, which Florida (2002) suggests as one of the three Ts - Talent, Technology, Tolerance – that contributes to build a local environment favourable to the economic performance. An open and tolerant society is able to accept a large share of external population, to attract new ideas and thus to enhance economic efficiency. As a measure of tolerance we use the share of population which, within the European Value Studies (EVS) questionnaire, has not mentioned the item "don’t like as neighbours: immigrants/foreign workers" as a possible answer. It should be noted that, on average, the European population seems quite tolerant (86.6% do not mention the item), although values below 50% can be found in the Austrian region of Kärnten (45%), in Severozapad (Czech Republic, 48%) and Oberpfalz (Germany, 49%), indicating considerable levels of intolerance towards immigrants and foreign population which may be detrimental for the economic performance (see Figure 7).

We have also controlled for the production structure of the economy with the inclusion of two alternative indicators of the regional relative specialisation in the manufacturing sectors and in the knowledge intensive sectors. It should be remarked that at the moment in Europe the regions specialised in manufacture are mainly located in the Eastern countries while the knowledge intensive regions belong the advanced Western countries[10]. This difference in the productive specialisation is expected to affect the regional productivity (Marrocu et al., 2010).

Another important feature of the local environment is the regional inhabited structure which allows controlling for the role played by the agglomeration economies. In this paper we use two alternative proxies: the settlement structure typology and the population density. The first proxy is a more complex indicator of regional hierarchy which distinguishes six types of regions according to two dimensions, density and city size: the less densely populated areas without centers take value one while the very densely populated regions with large centers, that is the urban areas, take the maximum value of six. In previous studies the territorial distribution of the population shows to have a positive impact on firms productivity: higher population density implies a higher and differentiated local demand, as well as the availability of a wider supply of local public services (Ciccone and Hall, 1996). The relationship between urban hierarchy and the distribution of the

[10] In manufacture, the top 5 regions are in Czech Republic, Hungary and Romania and among the top 10 there is only a German and an Italian region; in knowledge intensive sectors the top 10 regions are in UK, Luxembourg, Netherlands, France, Brussels.

creative class has been analysed by Lorenzen and Andersen (2009) for the case of city region in Northern European countries.

In the econometric analysis, we also control for other territorial features by including one dummy for the four largest countries in Europe, namely Germany, France, Great Britain and Italy. Finally, we control for the development level of the regional economies by introducing a dummy for the "convergence regions", defined as those regions with a per capita GDP lower than 75% of the EU average.

4. The estimation of regional total factor productivity

In this paper the regional economic performance is represented by total factor productivity. Being a measure of production efficiency, TFP allows to take into account regional differences in tangible inputs, such as physical capital stock and labour units. For this reason it is preferred to alternative measures like employment or income growth.

Regional TFP is estimated by following a quasi-growth accounting approach: rather than imposing a priori inputs' elasticities, obtained under the restrictive assumptions of constant returns to scale and perfect competition, these are first estimated from a regression model and then used within a standard growth account approach to compute TFP levels.

The regression model adopted is the log-linearized version of a traditional Cobb-Douglas production function, estimated over the period 1990-2007 for a pooled set of 13 manufacturing and services sectors (agriculture and non market services are excluded) for each of the 257 European regions:

$$y_{it} = \alpha_i + \alpha \; k_{it} + \beta \; l_{it} + \delta_t + u_{it} \qquad (1)$$

where lower-case letters represent log-transformed variables for value added, y, capital stock, k, and labour units, l; note that the capital stock has been constructed by applying the perpetual inventory method on investment series.

The panel model is estimated by TSLS (instruments are represented by one-period lagged capital and labour regressors) due to possible endogeneity problems and includes time dummies (δ_t) in order to account for macroeconomic shocks, common to all the regions. The productive inputs elasticities (reported in Table 3) are estimated in 0.40 for the capital stock and in 0.55 for the labour units. The comparison of the estimated TFP values across the European regions, depicted in Figure 8, not only confirms the well-known historical divide between Northern and Southern regions, but also highlights a striking economic gap between the regions belonging to the EU15 countries (the "old" Europe), on one hand, and the regions located in the 12 new accession countries (the "new" Europe). However, as argued in Marrocu et al. (2010), in the last decade Eastern European regions have exhibited quite a fast growth dynamics, which, at least in the traditional economic sectors, is driving the reduction of the still sizeable gap.

5. The role of human capital: empirical model and estimation issues

In this section we present and discuss the econometric analysis conducted to assess the effects on regional TFP of the creative class and high education and, most importantly, to consider the concurrent effects of the three categories of human capital proposed in section 2. The empirical model is specified as follows:

$$tfp_i=\alpha+\beta_1\, human\ capital_i+\beta\, set\ of\ controls_i + \varepsilon_i \qquad (2)$$

where both the dependent variable and the human capital one is expressed in per capita terms and log-transformed; for the basic specification we control for other factors, which have been proved to affect productivity, by including the stock of technological capital, foreign-born people as a percentage of resident population to proxy the degree of cultural diversity, the manufacturing specialization index and the settlement structure, which should account for varying degrees of rural/urban characteristics and thus for the presence of possible agglomeration externalities. To control for other characteristics of the local economy we also include a dummy for the four largest member countries and a dummy for the lagging regions belonging to the EU "convergence objective".

Endogeneity issues might be a potential concern for the estimation of model (2). However, note that, while it is hard to rule out reversal causality between output (or employment growth) and human capital, simultaneity between the latter and an efficiency measure, such as the TFP index we are using, is doubtful as the link is much more indirect and even if feedbacks effects are present it takes some years for human capital to be efficiency-enhancing. For this reason all the human capital variables refer to the year 2002 and the same happens for the control variables.[11] It could also be claimed that a five-year lag is not sufficient to remove endogeneity if TFP does not exhibit a certain degree of short-term variability. We check for this by estimating for each region univariate autoregressive models of order five for the TFP time series obtained for the period 1990-2007, as described in the previous section. The estimated fifth autoregressive coefficient, with an average value of nearly 0.14, turned out to be significant only in 21 cases out of 257; on the basis of this evidence we can argue that persistence in TFP is not inducing any endogeneity problems for our models. For our preferred specification (regression 4 of table 4) we also carried out a further check by splitting our sample into two groups of observations, top and bottom half TFP performing regions, and testing for significant differences in human capital variables elasticities between the two groups. We did not find evidence of any relevant difference and this can be considered an additional indication that there is no positive selection of graduate people into high-productive regions[12].

Model (2) was initially estimated by OLS and the spatial Robust LM tests[13], designed to detect the presence of spatial dependence in the error term or an omitted spatially lagged dependent variable, were carried out. The tests make use of a spatial weight matrix (W), whose entries are the inverse distance in kilometers between each possible couple of regions; following the suggestions in Keleijan-Prucha (2010), W is normalized by dividing each element by its maximum eigenvalue[14]. The tests provide evidence of spatially correlated residuals, so that model (2) is re-specified as a spatial error model with a mean equation as in (2) and a spatial AR model for the error term:

$$\varepsilon_i=\rho W\varepsilon_i+u_i \tag{3}$$

where ρ is spatial correlation coefficient, W is the weight matrix, defined as above, and u is an i.i.d. disturbance process[15].

[11] The only exception is the diversity proxy, which is consistently available for all our regions only for the period 2006-07, we will elaborate more on this variable when presenting the robustness analysis. Moreover, the education-creativity variables are available for all the 257 regions only for the 2002 year, so we cannot use previous lags. This lack of data also precludes a panel data analysis.

[12] The same kind of results were also obtained when we carried out the subsample analysis by dividing the whole sample into the 33%-67% or 25%-75% top-bottom performing regions.

[13] For a comprehensive description of spatial models and related specifications, estimation and testing issues refer to Le Sage and Pace (2009) and references therein.

[14] Such normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied.

[15] We also estimated the alternative spatial lag model as a robustness check, the results with an insignificant coefficient for the spatially lagged dependent variable confirm the adequacy of the spatial error specification.

6. Basic results and robustness analysis

In this section we present the results of the basic model reported in Table 4 and we also check for their robustness by considering other proxies for some of the control variables as reported in Table 5.

In order to compare our results with the findings of previous studies, we first estimate our models by including one human capital variable at a time: this strategy avoids the multicollinearity problem due to the high correlation between the two variables (for our sample the correlation coefficient between the graduates and the creatives is equal to 0.75). The spatial error model is estimated by ML and the results are reported in columns (1) and (2) of Table 4 for the two alternative measures of human capital. As expected, when they are included one at a time they are both significant and, on the basis of the estimated coefficients, 0.13 for the creatives and 0.10 for the graduates, one could claim that the first measure slightly outperforms the second one. However, as highlighted in section 2, if the creatives and the graduates variables are supposed to capture different aspects of the same phenomenon – potential and actual human capital skills – they should be considered as complements rather than as substitutes. Therefore, the effects of creatives and graduates should be estimated within the same regression model, otherwise one has to face the usual omitted variable problem. This is done in the model reported in column (3), but note that now the graduates turn out to be not significant as a consequence of the high correlation among the two regressors[16]. Again, this outcome may be erroneously interpreted as the creative group being more relevant than graduates for the regional economic performance.

On the basis of the results reported in columns (1)-(3) we argue that the estimation strategy followed so far in the empirical literature might lead to misleading conclusions and to questionable policy recommendations on the economic role played by the creativity and formal education components of human capital, if measurement matters concerning its disaggregation are overlooked.

In an attempt to reduce measurement problems and thus get more plausible estimated effects the key point is to include regressors derived from a more adequate definition of the relevant human capital variables. As explained in section 2 and represented in Figure 1, the graduates group has been disaggregated into non creative graduates and creative graduates, with the latter component forming up the creatives group when considered along with the bohemians.

[16] Note that for all the estimated models reported in table 4, model 3 is the one for which we found the highest variance inflation factors (VIF) for both human capital variables.

In the fourth specification reported in Table 4 we now include the three non-overlapping measures of human capital - creative graduates, non creative graduates and bohemians - in order to single out their individual contributions in enhancing regional efficiency. The results point out that the highly educated creative group is quite relevant in explaining total factor productivity (elasticity estimated in 0.161), followed by the non creative graduate group (elasticity of 0.043), while the bohemian category exhibits a negligible effect, confirming for the European regions the prominent importance of formal high education in determining economic outcomes.

With reference to our preferred specification (model 4), it is worth stressing that we are not considering education just in potential terms, as it is the case when one proxies human capital with educational attainment, but also in terms of actual utilized skills as the three human capital subgroups have been carefully defined on the basis of the occupations classification. According to our results the contribution of the non creative graduates seems more important for the creation of value added as they are a relevant component of the labour force, while the tasks they perform are evaluated in just a quarter of the effect due to the creative graduates in increasing the level of efficiency. This result is not surprising given that most of the non creative graduates are employed in occupations related to civil service, business and legal jobs (see Table 1)[17].

The result for the bohemians' group is the same as the one discussed by Glaeser (2005) for the case of US metropolitan areas: once the presence of graduated people is properly accounted for, the bohemians are no longer relevant.

However, it could be claimed that the Bohemians' result is driven by the assumption we made in defining our human capital categories, for this group we hypothesized that is talent, rather than formal education, the most relevant distinguishing feature. If a measurement problem is present due to some Bohemians being also graduates, this should yield even more unfavourable evidence. Since, as emphasised in section 3, we do not have additional information to check for this aspect of our data, we conduct a simple robustness exercise by assuming that such a measurement error could be on average equal to 20% of people in the Bohemian group being misclassified; since they are actually graduate workers, they should rather be included in the creative graduate group[18]. We, therefore, re-disaggregate our data for the human capital categories accordingly. The results,

[17] As far as the legal profession is concerned, several studies have shown that the presence of a large number of lawyers "harms" economic performances since they are mostly engaged in rent seeking activities (see, among others, Datta and Nugent, 1986; Murphy et al., 1991).

[18] For Italy, using the labour force survey micro data, we have calculated that the share of graduates in some occupations included in the Bohemians group is 18%.

reported in the first column of table 5, are very robust to this variation in the classification[19] and confirm the evidence previously presented for the preferred model specification.

It is plausible to think that the role played by Bohemians is somewhat indirect as their presence might signal – especially to creative graduates – a more open and stimulating working environment. However, they are significantly outperformed in our estimated models by foreign-born people, who are included to approximate the cultural diversity factors. As stated in section 2, this variable is expected to capture the beneficial effects of a more tolerant, inclusive and open environment that, in turn, facilitates the creation of new ideas and the development of more talented skills by taking advantage of the diversity potential (Bellini et al., 2008, Florida et al., 2008, Wedemeier, 2010).

As anticipated at the beginning of this section for the foreign-born people there is no data available for the 2002 year for all the new accession countries regions, so that we are constrained to use more recent data. However this, again, could rise some endogeneity concerns. To check for this we re-estimate our preferred basic specification (model 4, table 4) by using census data of foreign population for the year 2001, which, regrettably, is available for NUTS2 regions only for a reduced subsample (193 regions out of the 257)[20]. The estimated coefficient (the model is reported in the second column of table 5), positive and significant, is greater than the one reported for the last model of table 4 (0.76 versus 0.56), but note that the human capital variables are pretty robust, exhibiting only slightly reduced elasticities with respect to the preferred specification. Thus, using the most recent data on residents born in an another country does not seem to alter in a remarkable way the estimates for the whole sample [21]. For this reason in the subsequent analysis we prefer to keep all the 257 regional observations and account for cultural diversity using the 2006-07 data for foreign born people.

We also attempt to control for cultural diversity factors by considering a direct measure of tolerance, given by the percentage of resident population that do not dislike having immigrant/foreign people as neighbours. This new control is included in regression 3 of table 5, although it shows a positive coefficient estimates it is not significant at conventional levels, and it remains so even when we consider an alternative specification (not reported) where it is included in place of the share of foreign-born population. This result may be due to the fact that the data

[19] We have also experimented with different proportions of misclassification error (in the range 10-30%) and model (4) results were extremely robust.
[20] No data on foreign population is available for Malta, Belgian, German, Greek regions.
[21] Note also that the approach suggested in Ottaviano and Peri (2006) and Bellini et al. (2009), based on the use of shift-share instrumental variables for the diversity regressors, is not viable in our case, as it requires data from a far distant previous period disaggregated by immigrants' country of origin, which is not available for all the regions included in our sample.

available for directly proxing tolerance are not informative enough to capture such a complex phenomenon; a deeper investigation of the "tolerance" aspects of the local economic environment is left for future research.

Turning to the other local economy controls, a positive significant effect, rather robust across of the alternative specifications considered, is found for the technology stock accumulated in the regional economy, which is measured by patents (0.068), a very similar estimate for the technological capital was also reported in Dettori et al. (2010) for the case of the European regions belonging to the EU15 countries plus Switzerland and Norway.

As the codified knowledge creation process may depend on the industrial structure, in our models we also include the index of manufacture specialization, this turned out to be negatively associated with the TFP levels, signalling that a regional industrial structure specialized in manufacture sectors does not seem to favour efficiency enhancements. This may be due to the fact that the innovative drive of such productions is to be considered by now accomplished, especially in the more advanced Western economies, as we have remarked in section 3. On the other hand, efficiency gains might be expected for economies specialized in knowledge intensive sectors, in model (4) of table 5 we test this conjecture by including the corresponding specialization index; although the coefficient sign is now positive, as expected, it is significant only at the 17% level. A possible explanation for this result is that the differences in the agglomeration economies due to the production structure are more adequately captured by the settlement structure. This variable turns out to be positively and significantly correlated with TFP, signalling that more urban and densily populated regions are associated with higher productivity levels (estimated coefficient 0.021), thanks to the presence of diversified jacobian-type agglomeration externalities especially in the service sectors.

Finally we control for other specific local characteristics by including two dummies for the convergence regions and for the four largest countries, which exhibit the expected negative and positive sign respectively. This provides further evidence that holding constant the intangible efficiency determinants, TFP is on average lower in the converging regions (see also Figure 8), while being located in the four largest countries counterbalances the previous effect for the poorer regions and increases the productivity for the richer ones.

In sum, we think that the analysis presented provides convincing and robust evidence on the complementary role played by the two main dimensions of human capital - formal education and talent - which are often combined in the tasks performed by the very same people within a productive environment. At the same time our results show that once we adequately control for the educational attainment the bohemians component does not affect the regional economic performance.

7. Concluding remarks

After more than three decades of theoretical and empirical research on economic growth, the role of human capital as its most important determinant has by now become undisputed. In recent years the focus has been actually shifted to investigating its specific characteristics and components even further in order to reach a better understanding of the interactions between human capital, geographical features and firms localization strategies or to assess which of its components are more growth enhancing.

After the success of the Florida (2002) book, which suggests that what really matters are actual rather than potential skills, great attention has been devoted to the creativity component of human capital from both an academic and a policymaker perspective. The European Commission declared the year 2009 as the year of creativity, thus emphasising its potential impact on regional economic performance.

Following Florida's suggestion, some recent contributions have focussed on the effects on local economic performance of the creative abilities required by specific occupations, such as the ones in the fields of sciences, engineering, education, culture, arts and entertainment. However, the empirical analyses carried out so far was not based on a clear definition and measurement of the education and creativity components of human capital, so that the evidence provided on their effects may be unreliable due to omitted variable problems or, at the least, to multicollinearity.

In this paper we propose a disaggregation of human capital into three non-overlapping categories in order to overcome the measurement problem. The three categories of *creative graduates*, *bohemians* and *non creative graduates* are identified by combining the information on educational attainments with the one related to the actual occupations in an attempt to account for the concurrent effects of both potential and on-the-job utilized skills.

Since the three groups do not overlap and they are supposed to capture different characteristics of the human capital phenomenon, all of them are included in our empirical models and this makes our estimated impacts robust to the omitted variable problem. As a matter of fact this was an issue in previous empirical analyses because in order to avoid multicollinearity, induced by the inclusion of the overlapping variables "graduates" and "creativity class", these variables were included one at a time, thus resulting in biased estimates if education and creativity are expected to be both complementary determinants, rather than substitutes, in determining economic outcomes.

Once the three human capital categories have been identified, we evaluate their effect on TFP for a large set of 257 regions belonging to EU27. The TFP variable has been derived within a quasi-growth accounting approach from estimated production function models without requiring the imposition of restrictive assumptions on factors' elasticities. TFP is our preferred indicator of economic performance as it is a direct measure of efficiency; moreover, its use as the dependent variable in our empirical models makes endogeneity problems, due to simultaneity and feedback effects, much less likely than in the case of other measures of economic outcomes, such as output or employment. We also guard against possible endogeneity by using five-year lagged variables for both human capital regressors and controls. A disaggregation of the entire sample into subsamples for top and bottom performing regions has also ruled out the possibility of positive selection of graduates into high-TFP areas.

The effects of human capital are estimated from spatial error models controlling for regional geographical features and for characteristics of the local environment, such as cultural diversity, technological capital, industrial structure and urban/rural settlement pattern.

Our main results indicate that the highly educated creative group is the most relevant one in explaining production efficiency, followed by the non creative graduate one, which exhibits an effect of just a quarter the impact of the first group. Arguably, the role played by non creative graduates is mostly confined to the formation of value added. This result is mainly driven by the fact that most of the non creative graduates are employed in occupations related to civil service, business and legal jobs. The bohemians turn out to be not significant once we control for the presence of the creative graduated group.

The evidence provided on the diversified effects of human capital categories are robust to a thorough series of robustness checks, which have also substantiated the relevant influence exerted by technological capital, cultural diversity, industrial structure and settlement pattern, thus providing further empirical support to the claim that an innovative, open, inclusive and culturally mixed environment is becoming more and more crucial for productivity enhancements.

We think that the analysis presented in this paper offers a novel contribution to the debate on the different but complementary role played by education and creativity in determining regional economic performance, once these are properly defined and when controlling at the same time for specific characteristics of the local environment.

In conclusion, our key result is that higher education is the most important factor in driving economic outcomes, although significant differences emerge among the actual occupations of graduate workers. The most effective role is played by the graduates employed in creative occupations characterised by a higher rate of production and diffusion of new ideas, innovations and knowledge. On the other hand, a significant but lower efficiency enhancing effect is due to graduates working in other occupations. In this picture there is no room left for an independent effect on productivity exerted by the bohemian group; creativeness per se does not seem to influence regional economic performance, albeit it may contribute to create a favourable and enjoyable environment.

From a policymaking perspective, these results call for more effective national and regional policies aimed at increasing the access to high education and at supporting university degrees more linked to sciences, engineering and education fields; at the local level urban planning should aim at ensuring that European regions become more attractive for skilled people and not just for creative individuals.

References

Andersen K.V., H.K. Hansen, A. Isaksen and M. Raunio (2010) Nordic City Regions in the Creative Class Debate: Putting the Creative Class Thesis to a Test, *Industry and Innovation*, 17, 215-240.

Asheim B. and H.K. Hansen (2009) Knowledge bases, talents, and contexts: On the usefulness of the creative class approach in Sweden, *Economic Geography*, 85, 425–442.

Atkinson R. and H. Easthope (2009) The Consequences of the Creative Class: The Pursuit of Creativity Strategies in Australia's Cities, *International Journal of Urban and Regional Research*, 33,64-79.

Audretsch D. and M. Feldman (2004) Knowledge spillovers and the geography of innovation, in Henderson V. and J.F. Thisse (eds.) *Handbook of Regional and Urban Economics: Cities and Geography*. Amsterdam: Elsevier.

Bellini E., G.I. Ottaviano, D. Pinelli and G. Prarolo (2008) Cultural Diversity and Economic Performance: Evidence from European Regions, *HWWI Research Papers* 3-14.

Benhabib J. and M. Spiegel (1994) The role of Human Capital in Economic Development: evidence from aggregate cross-country data, *Journal of Monetary Economics*, 34, 143-174.

Berry C.R. and E. Glaeser (2005) The Divergence of Human Capital Levels across Cities, *Papers in Regional Science*, 84, 407-444.

Boschma R.A. and M. Fritsch (2009) Creative class and regional growth. Empirical evidence from seven European countries, *Economic Geography*, 85, 391-423.

Ciccone A. and R. Hall (1996) Productivity and the density of economic activity, *American Economic Review*, 86, 54-70.

Datta S.K. and J.B. Nugent (1986) Adversary Activities and Per Capita Income Growth, *World Development*, 14, 1457-1461.

Dettori B., E. Marrocu and R. Paci (2010) Total Factor Productivity, intangibile assets and spatial dependence in the European regions, *Regional Studies*, forthcoming, DOI: 10.1080/00343404.2010.529288.

Di Liberto A. (2008) Education and Italian regional development, *Economics of Education Review*, 27, 94–107.

European Commission (2009) 6th Progress Report on Economic and Social Cohesion. Brussels.

Fischer M.M., M. Bartkowska, A. Riedl, S. Sardadvar and A. Kunnert (2009a) The impact of human capital on regional labor productivity in Europe, *Journal Letters in Spatial and Resource Sciences*, 2, 97-108.

Fischer M.M., T. Scherngell and M. Reismann (2009b) Knowledge spillovers and total factor productivity. Evidence using a spatial panel data model, *Geographical Analysis*, 41, 204-220.

Florida R. (2002) *The rise of the creative class and how it's transforming work, leisure, community, and everyday life*. New York: Basic Books.

Florida R., C. Mellander and K. Stolarick (2008) Inside the black box of regional development: Human capital, the creative class and tolerance, *Journal of Economic Geography*, 8, 615–49.

Glaeser E. (2005) Review of Richard Florida's the rise of the creative class, *Regional Science and Urban Economics*, 35, 593-596.

Glaeser E., J. Kolko and A. Saiz (2001) Consumer City, *Journal of Economic Geography*, 1, 27-50.

Griliches Z. (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth, *The Bell Journal of Economics*, 10, 92-116.

Jacobs J. (1969) *The Economies of Cities*. New York: Random House.

Kelejian H.H. and I.R. Prucha (2010) Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances, *Journal of Econometrics*, 157, 53-67.

Krugman P. (1991) Increasing Returns and Economic Geography, *Journal of Political Economy*, 99, 483-499.

Le Sage J.P. and R.K. Pace (2009) *Introduction to Spatial Econometrics.* Boca Raton: CRC.

Lorenzen M. and K.V. Andersen (2009) Centrality and creativity: Does Richard Florida’s creative class offer new insights into urban hierarchy? *Economic Geography*, 85, 363–390.

Lucas R.E. (1988) On the mechanics of economic development, *Journal of Monetary Economics*, 22, 3–42.

Mankiw N.G., D. Romer and D. Weil (1992) A contribution to the empirics of economic growth, *Quarterly Journal of Economics*, 107, 407-437.

Markusen A. (2006) Urban development and the politics of a creative class: Evidence from the study of artists, *Environment and Planning A*, 38, 1921–1940.

Marlet G. and C. van Woerkens (2007) The Dutch Creative Class and How It Fosters Urban Employment Growth, *Urban Studies*, 44, 2605-26.

Marrocu E., R. Paci and S. Usai (2010) Productivity growth in the Old and New Europe: the role of agglomeration externalities, *CRENoS WP* 2010/24.

McGranahan D. and T. Wojan (2007) Recasting the creative class to examine growth: Processes in rural and urban counties, *Regional Studies*, 41, 197–216.

Mellander C. and R. Florida (2007) The Creative Class or Human Capital – Explaining Regional Development in Sweden. *KTH/CESIS WP 79*.

Murphy K.M., A. Shleifer and R.W. Vishny (1991) The Allocation of Talent: Implications for Growth, *Quarterly Journal of Economics*, 106, 503-530.

Nathan M. (2007) The Wrong Stuff? Creative Class Theory and Economic Performance in UK Cities, *Canadian Journal of Regional Science*, 30, 433-49.

Nathan M. and N. Lee (2011) Does cultural diversity help innovation in cities? Evidence from London firms, *SERC Discussion Paper 69*.

Ottaviano G. and G. Peri (2006) The Economic Value of Cultural Diversity: Evidence from US Cities, *Journal of Economic Geography*, 6, 9-44.

Peck J. (2005) Struggling with the creative class, *International Journal of Urban and Regional Research*, 29, 740-770.

Ramos R., J. Suriñach and M. Artís (2010) Human capital spillovers and regional economic growth in Spain, *Papers in Regional Science*, forthcoming.

Rauch J. (1993) Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities, *Journal of Urban Economics*, 34, 380-400.

Rodriguez-Pose A. and Crescenzi R. (2008) Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe, *Regional Studies*, 42, 51-67.

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

Villalba E. (2008) On Creativity. Towards an Understanding of Creativity and its Measurements, *JRC*, European Commission.

Wedemeier J. (2010) The Impact of Creativity on Growth in German Regions , *FEEM WP*, SUSDIV PAPER 14.2010

Appendix 1. Regions and NUTS level

Code	Country	NUTS	Regions
AT	Austria	2	9
BE	Belgium	2	11
BG	Bulgaria	2	6
CY	Cyprus	0	1
CZ	Czech Republic	2	8
DE	Germany	2	39
DK	Denmark	0	1
EE	Estonia	0	1
ES	Spain (a)	2	16
FI	Finland	2	5
FR	France (a)	2	22
GR	Greece	2	13
HU	Hungary	2	7
IE	Ireland	2	2
IT	Italy	2	21
LT	Lithuania	0	1
LU	Luxembourg	0	1
LV	Latvia	0	1
MT	Malta	0	1
NL	Netherlands	2	12
PL	Poland	2	16
PT	Portugal (a)	2	5
RO	Romania	2	8
SE	Sweden	2	8
SI	Slovenia	0	1
SK	Slovakia	2	4
UK	United Kingdom	2	37

(a) Territories outside Europe are not considered

Appendix 2. Data sources and definition

Variable	Label	Description	Primary Source
Value added	Y	Millions euros prices 2000; 1990-2007	Cambridge Econometrics
Capital stock	K	Millions euros prices 2000; 1990-2007	Own calculation
Units of labour	L	Unitys of labour, thousands; 1990-2007	Cambridge Econometrics
Total Factor Productivity	TFP	TFP level, 2007	Own estimation
Creative graduates	CG	Creative core employment, thousands (see Table 1 for ISCO classification); 2002	Labour Force Survey
Bohemians	B	Creative bohemians employment, thousands (see Table 1 for ISCO classification); 2002	Labour Force Survey
Creatives	C	Creative graduates plus Bohemians, thousands; 2002	Labour Force Survey
Graduates	G	Employment with qualification level ISCED 5-6, thousands; 2002	Eurostat
Non creative graduates	NCG	Differences between Graduates and Creative graduates employment, thousands; 2002	Own calculation
Technological capital	TK	Patents stock, years 2000-2004	Crenos on EPO
Diversity	DIV	Population born in another country, thousands; 2006-2007 (alternative proxy: foreign population over resident population, Census 2001)	Eurostat
Manufacture specialisation	MAN	Specialisation index of manufacturing employment, 2002	Eurostat
Knowledge specialisation	KIS	Specialisation index of knowledge intensive service employment, 2002	Eurostat
Settlement Structure Typology	SST	1=less densely populated without centres, 2=less densely populated with centres, 3=densely populated without large centers, 4=less densely populated with large centres, 5= densely populated with large centres, 6=very densely populated with large centres; 1999	ESPON project 3.1 BBR
Population density	DEN	Population per km^2, thousands; 2002	Eurostat
Tolerance	TOL	Population that do not mention "don't like as neighbours: immigrants/foreign workers", %	EVS
Dummy convergence regions	DCONV	Dummy for the "convergence regions" (<75% EU GDP average)	Eurostat
Dummy large countries	D4	Dummy for the 4 largest EU countries (DE, FR, UK, IT)	Own calculation

Table 1. Creatives and Graduates

Code (ISCO 88)	Occupation
A. Creative graduates (core creative class)	
211	Physicists, chemists and related professionals
212	Mathematicians, statisticians and related professionals
213	Computing professionals
214	Architects, engineers and related professionals
221	Life science professionals
222	Health professionals (except nursing)
231	College, university and higher education teaching professionals
232	Secondary education teaching professionals
233	Primary and pre-primary education teaching professionals
234	Special education teaching professionals
235	Other teaching professionals
243	Archivists, librarians and related information professionals
244	Social science and related professionals
B. Bohemians	
245	Writers and creative or performing artists
347	Artistic, entertainment and sports associate professionals
521	Fashion and other models
C. Non creative graduates *(non exhaustive list)*	
111	Legislators
112	Senior government officials
121	Directors and chief executives
131	General managers
223	Nursing and midwifery professionals
241	Business professionals
242	Legal professionals
graduates may also be occupied in:	
3	Technicians and associate professionals

International Standard Classification of Occupations (ISCO 88)

Table 2. Summary statistics

Variable		Min	Max	Mean	Std. Dev.	Coeff. Var.
Graduates	a	4.53	59.20	12.52	5.73	0.46
Creatives	a	1.25	12.76	5.90	2.05	0.35
Creative graduates	a	1.17	10.93	5.26	1.70	0.32
Non creative graduates	a	0.00	51.41	7.25	4.64	0.64
Bohemians	a	0.03	4.46	0.63	0.50	0.79
Technological capital	b	0.00	4.14	0.47	0.60	1.27
Diversity	c	0.01	37.59	6.96	5.81	0.83
Tolerance	c	45.29	100.00	86.69	10.06	0.12
Manufacture specialisation	d	-0.59	0.35	-0.04	0.19	-4.75
Knowledge specialisation	d	-0.57	0.38	-0.07	0.18	-2.73
TFP		2.39	28.97	11.12	4.00	0.36

(a) % values over population 25 and over
(b) per thousands population
(c) % values over population
(d) normalised index [-1 , +1]

Table 3. Measuring total factor productivity

Dependent variable: value added	
Estimation method: TSLS	
Sample period: 1990-2007, T=18; N=257; S=13; N*S*T=60138 §	
Capital stock	0.396 ***
	(0.025)
Labour units	0.546 ***
	(0.023)
Time effects	included
R^2	0.785

Robust standard errors in parenthesis; level of significance: *** 1%, ** 5%, * 10%
Instruments are one-year lagged explanatory variables
§ The balanced panel consists of 13 sectoral series for each of the 257 regions

Table 4. Total factor productivity and human capital

Dependent variable: total factor productivity				
Spatial error models	**1**	**2**	**3**	**4**
Human capital				
Graduates	0.100 ***		0.057	
	(0.039)		*(0.047)*	
Creatives		0.130 ***	0.091 *	
		(0.047)	*(0.056)*	
Creative graduates				0.161 ***
				(0.051)
Non creative graduates				0.043 ***
				(0.016)
Bohemians				-0.027
				(0.024)
Control variables				
Technological capital	0.073 ***	0.074 ***	0.069 ***	0.068 ***
	(0.013)	*(0.013)*	*(0.013)*	*(0.013)*
Diversity	0.058 ***	0.054 ***	0.057 ***	0.056 ***
	(0.014)	*(0.014)*	*(0.014)*	*(0.014)*
Manufacture specialization	-0.244 ***	-0.241 ***	-0.230 ***	-0.240 ***
	(0.072)	*(0.072)*	*(0.072)*	*(0.072)*
Settlement structure	0.023 ***	0.018 **	0.018 **	0.021 **
	(0.008)	*(0.009)*	*(0.009)*	*(0.009)*
Dummy 4 largest countries	0.138 ***	0.141 ***	0.147 ***	0.151 ***
	(0.033)	*(0.033)*	*(0.033)*	*(0.033)*
Dummy convergence regions	-0.215 ***	-0.230 ***	-0.224 ***	-0.227 ***
	(0.042)	*(0.042)*	*(0.043)*	*(0.042)*
Spatial error correlation coefficient	0.895 ***	0.904 ***	0.895 ***	0.893 ***
	(0.074)	*(0.067)*	*(0.074)*	*(0.075)*
Square correlation, actual and fitted values	0.806	0.805	0.808	0.814

Estimation method: ML. Observations: 257 regions. All regressions include a constant term
Human capital variables, diversity and technological capital are log-transformed and in per capita values.
The spatial weight matrix is the inverse distance matrix, max-eigenvalue normalized
Robust standard errors in parenthesis; level of significance: *** 1%, ** 5%, * 10%

Table 5. Total factor productivity and human capital - robustness analysis

Dependent variable: total factor productivity					
Spatial error models	**1**	**2**	**3**	**4**	**5**
Human capital					
Creative graduates (a)	0.167 ***	0.156 ***	0.159 ***	0.158 ***	0.180 ***
	(0.052)	*(0.058)*	*(0.051)*	*(0.053)*	*(0.051)*
Non creative graduates	0.043 ***	0.030 *	0.041 **	0.045 ***	0.042 ***
	(0.016)	*(0.018)*	*(0.016)*	*(0.017)*	*(0.016)*
Bohemians (a)	-0.031	-0.025	-0.026	-0.019	-0.022
	(0.025)	*(0.028)*	*(0.024)*	*(0.025)*	*(0.025)*
Control variables					
Technological capital	0.068 ***	0.082 ***	0.068 ***	0.052 ***	0.068 ***
	(0.013)	*(0.015)*	*(0.013)*	*(0.012)*	*(0.013)*
Diversity	0.056 ***		0.056 ***	0.068 ***	0.054 ***
	(0.014)		*(0.014)*	*(0.013)*	*(0.014)*
Diversity 2001		0.076 ***			
		(0.022)			
Tolerance			0.048		
			(0.099)		
Manufacture specialization	-0.238 ***	-0.172 *	-0.239 ***		-0.230 ***
	(0.072)	*(0.091)*	*(0.072)*		*(0.072)*
Knowledge specialization				0.185	
				(0.136)	
Settlement structure	0.021 **	0.020 **	0.021 **	0.015 *	
	(0.009)	*(0.010)*	*(0.009)*	*(0.009)*	
Population density					0.016
					(0.013)
Dummy 4 largest countries	0.151 ***	0.181 ***	0.150 ***	0.155 ***	0.163 ***
	(0.033)	*(0.044)*	*(0.033)*	*(0.035)*	*(0.033)*
Dummy convergence regions	-0.227 ***	-0.263 ***	-0.224 ***	-0.232 ***	-0.227 ***
	(0.042)	*(0.056)*	*(0.043)*	*(0.043)*	*(0.043)*
Spatial error correlation coefficient	0.893 ***	0.896 ***	0.893 ***	0.917 ***	0.885 ***
	(0.075)	*(0.073)*	*(0.075)*	*(0.058)*	*(0.080)*
Square corr., actual and fitted values	0.814	0.826	0.814	0.805	0.811
Observation	257	193	257	257	257

Estimation method: ML for spatial error models. All regressions include a constant term

Human capital variables, diversity and technological capital are log-transformed and in per capita values.

The spatial weight matrix is the inverse distance matrix, max-eigenvalue normalized

Robust standard errors in parenthesis; level of significance: *** 1%, ** 5%, * 10%

(a) In model 1 the creative graduates variable is increased by an amount equal to 20% of the bohemians variable, the latter is reduced accordingly; see section 5.2 for details

Figure 1. Graduates and creatives
(% values over population 25 and over, 2002).

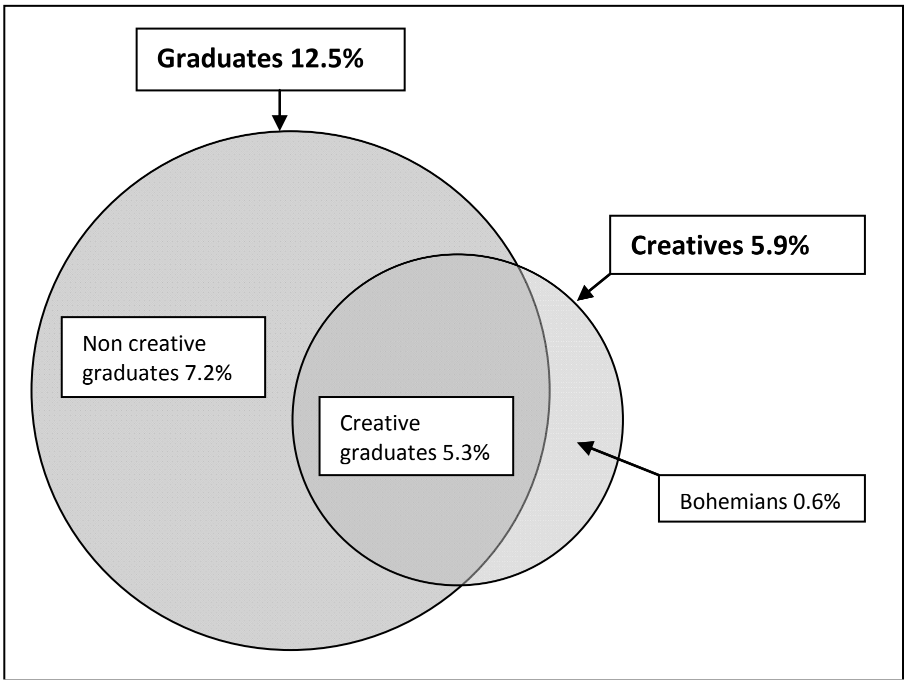

Figure 2. Creative graduates
(Creative graduates employment over population 25 and over; % , 2002)

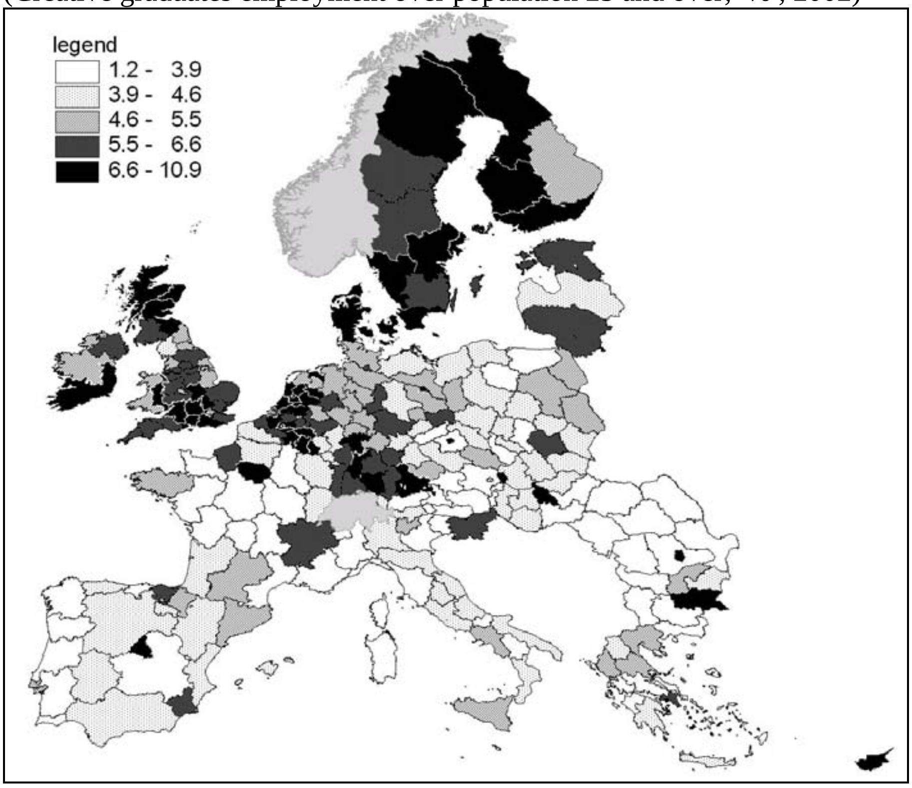

Figure 3. Bohemians
(Creative bohemians employment over population 25 and over; % , 2002)

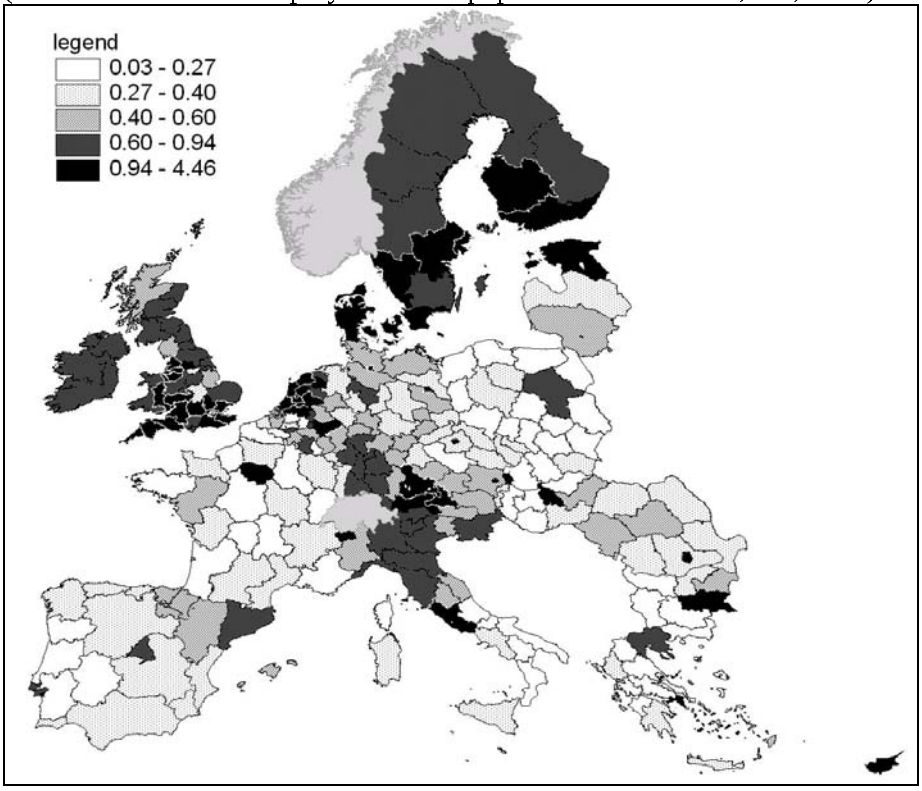

Figure 4. Non creative graduates
(Graduates minus creative graduates employment, over population 25 and over; %, 2002)

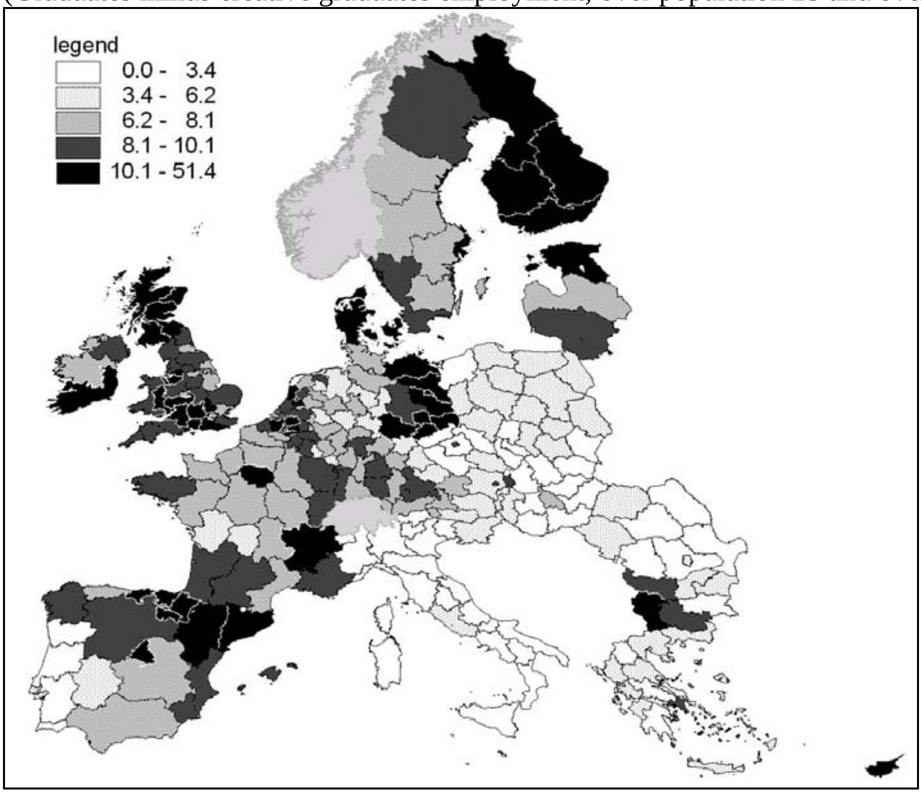

Figure 5. Technological capital
(Patent at EPO per thousand population, stock years 2000-2004)

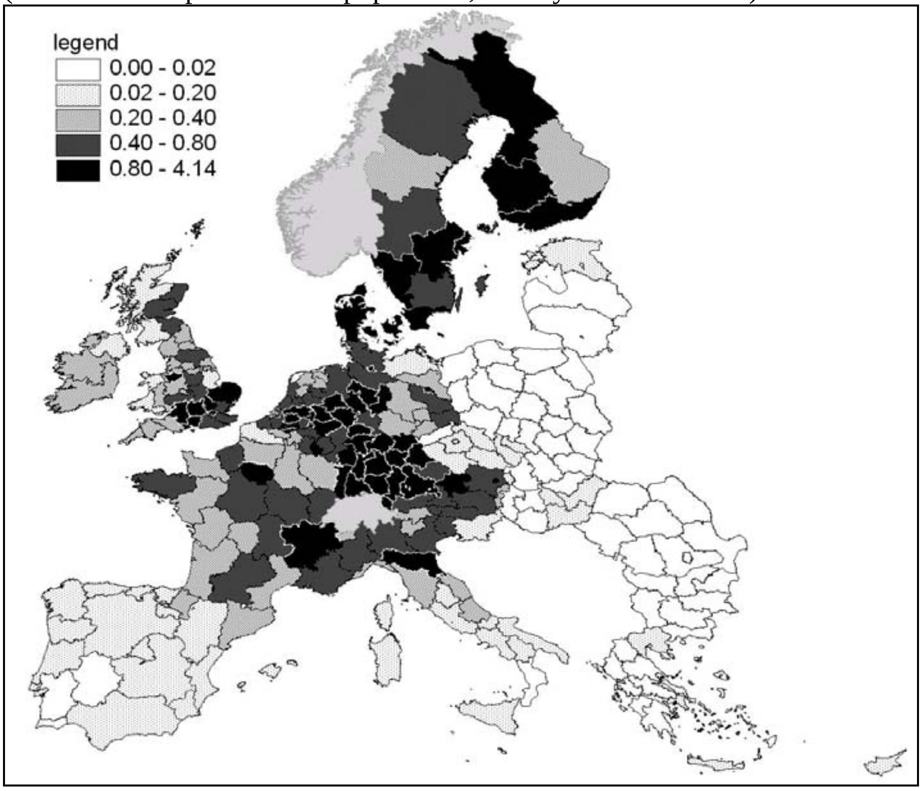

Figure 6. Diversity
(Population born in another country over population, %, 2006-2007)

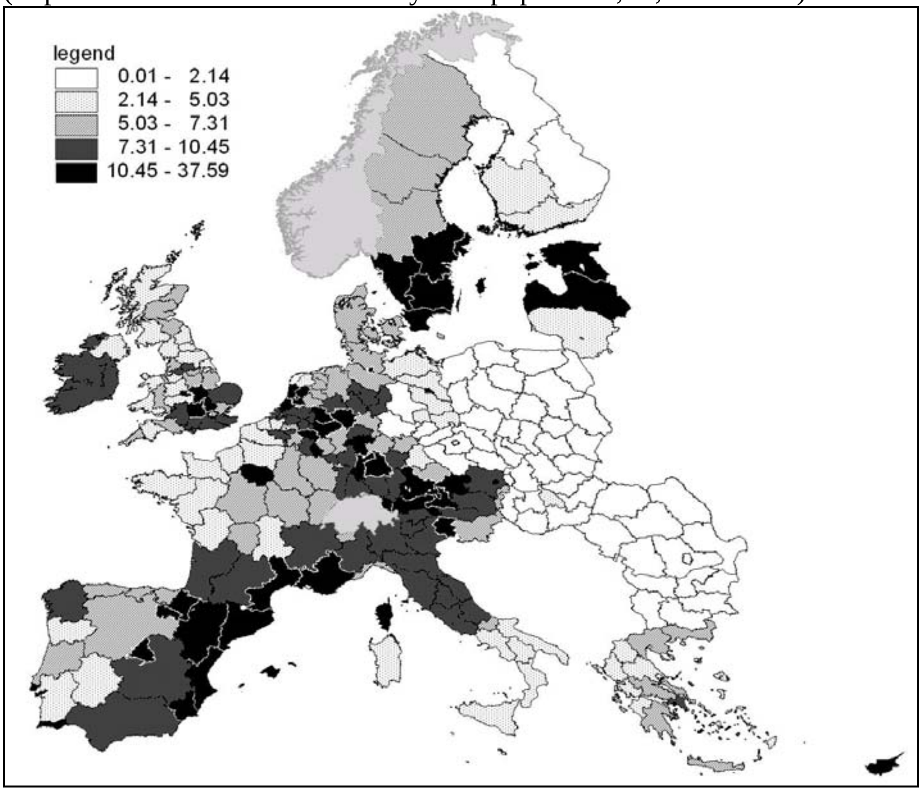

Figure 7. Tolerance
(Population that do not mention
"don't like as neighbours: immigrants/foreign workers", %)

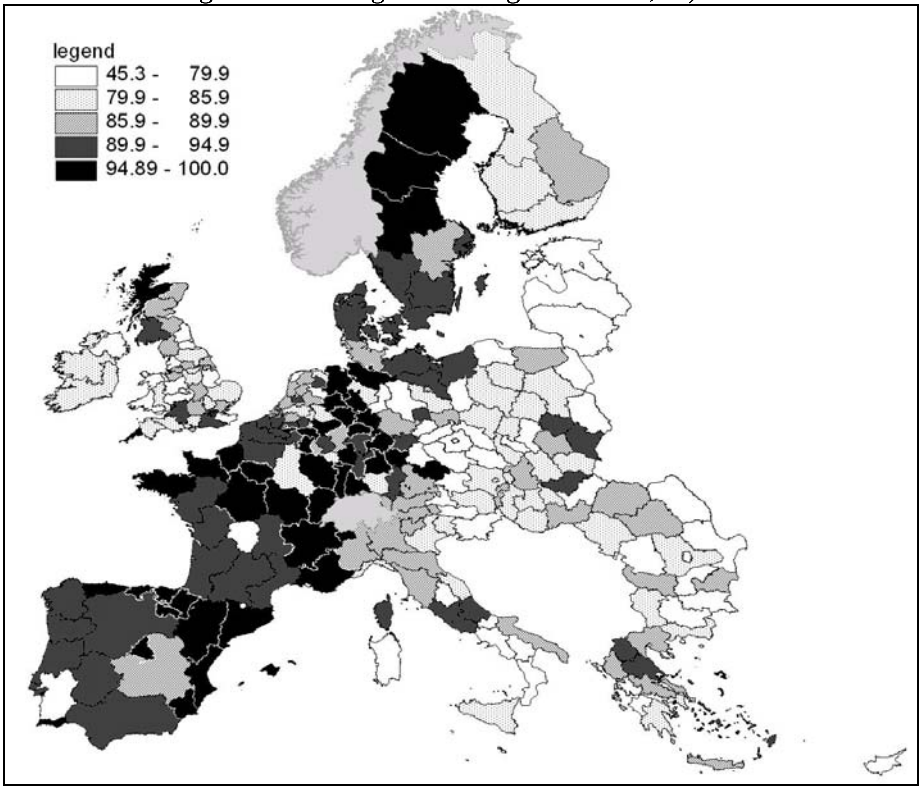

Figure 8. Total Factor Productivity
(index Europe=100, 2007).