Education or Creativity: what matters most for economic performance?

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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 highly educated people working in creative occupations are the most relevant component in explaining production efficiency, non creative graduates exhibit a lower impact, while the bohemians do not show a significant effect 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

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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, 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 completely adequate 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).

However, the definition of creative class suggested by Florida has been criticised, on one hand, for being too broad to enable a practical operationalization of such a concept in empirical models aimed at assessing the role of creativity as an engine of economic development. On the

[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 al. (1991) remarked that countries with a higher proportion of engineers grow faster, whereas countries with a higher proportion of lawyers grow more slowly.

other, its huge overlapping with the concept of human capital does not allow to gain a clear understanding of the relationships between creativity and education and their effects on regional economic growth.

McGranahan and Wojan (2007) emphasise that Florida's creative class not only entails high education occupations but also encompasses some technician occupations that, over time, have acquired important decision-making responsibilities, but such a high level of aggregation may indeed lead to low "construct validity"[2]. For this reason the authors propose a narrow definition of the creative class – the *recast* creative class – mainly based on the creativity content of occupations derived from the US Occupational Information Network; occupations that require "little creative thinking" and are more reproduction and execution oriented are therefore dropped from the broad definition. This allows to reduce the high heterogeneity among creative occupations, which is likely to lead to misleading results in the empirical analysis (Comunian et al. 2010).

In applied contributions several attempts have been made in order to reach a workable concept of creativity, but this, being heavily dependent on the specific aim of the study one cares to consider, far from clarifying things, have made the overall picture even more blurred.

We believe that at the core of this definition problem is the issue of the relationship between creativity and education. As a matter of fact, 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 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 one's 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. While in his initial contribution Florida claimed that creativity potential was by no means dependent on having acquired a high level of formal education, in his most recent studies (Florida et al., 2008) he acknowledges Glaeser's critique and accepts the idea that they are somehow complementary in driving regional development.

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 is the strong overlapping between graduates and creatives, although acknowledged in the literature, this problem is remained mostly overlooked in

[2] Markusen (2006) is even more critical and sees the definition of creative class as an artificial construction which assembles a number of occupations with very little in common.

the empirical applications. As a matter of fact, most of the individuals included in the creative class 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 econometric analyses the unclear identification of the education and creativity components generates a measurement problem, leading to confusing evidence as the human capital effects are inadequately 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. In this way if creativity is really making formal education more economically valuable this should show up in finding an additional effect for creative workers over and above the one associated with traditional human capital measures, thus reconciling Florida's and Glaeser's "opposite" views.

In our empirical analysis, 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 human capital which applies talent and that which does not 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 highly skilled people in a specific area (Glaeser et al., 2001; Dettori et al., 2010). Assessing the role of education and creativity while controlling at the same time for external institutional and economic factors is particularly important in the European context, as this is characterized by a high degree of regional heterogeneity (Asheim and Hansen, 2009). Therefore, we test the robustness of our results by accounting for several important elements of the regional economy (like the availability of technological capital, the degree of tolerance and cultural diversity, the industrial structure, the regional hierarchy and the first nature geographical characteristics), 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 to deal with 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 along with some robustness checks for human capital indicators. Section 7 entails a wider robustness analysis on model specification and on alternative control variables. Section 8 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 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, 2011), 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 definition of creative class, 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 (2011) for Sweden. Similar results are found by McGranahan and Wojan (2007) using a 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 alternatively 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. Note, however, that both in Florida et al. (2008) and in Mellander and Florida (2011), while a great care has been devoted to account for differences among the various occupations, the crucial point regarding to what extent the effects of creativity are inflated by the concurrent presence of graduates has remained completely unaddressed.

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 ambiguous 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 along the lines initially suggested by Florida. However, as mentioned in the introduction, the Florida's concept of creative class is quite broad and includes a very wide range of occupations, from the ones characterized by the most innovative tasks to the ones that involve just mere executive duties. Moreover, in Florida's contributions the detailed codes of the occupations included in the creative class are not reported so it is difficult to exactly reproduce his classification using other data sources. Furthermore, in the existing literature each contribution has used slightly different definitions of creative class depending on the territorial coverage and thus on data sources used.

In this paper we aim at considering all the EU countries and the only data source available for individual occupations is the European Labour Force Survey (ELFS). Therefore, we follow the classification of creative class presented in the European Commission Report (2009) based on the International Standard Classification of Occupations (ISCO, 88) and available in the ELFS. This classification consider the two groups of "creative core" and "bohemians" which have the highest creativity score as they include professions like architects, engineers, college, university and higher education professionals, cultural and artistic occupations, just to mention a few. The European Commission classification is similar to the one used by Boschma and Fritsch (2009) but, differently from the latter, it does not include the "creative professionals" (legislators, business and legal professionals and a great deal of technicians), who definitely carry out much lower creative tasks.

On the basis of the European Commission classification in Table 1 we decompose the category usually called Creative Class (CC) 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,

[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.

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 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 on local performance of the creative component: 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 a 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 check whether such a possible measurement error affects our results.

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). 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

[4] Ideally we would need individual 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 anonymisation procedures. Contributions based on micro individual data have been proposed for few countries where these detailed information are available: Comunian et al 2010 for UK, Mellander (2008) for Sweden, King et al. (2010) for US, Canada and Sweden.

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 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 aims at distinguishing this category from the creative groups. Some of these occupations (Major group 1 Legislators, senior officials and managers; business professional, legal professionals) are sometimes 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.

In summary, by combining the information on educational attainments with the one related to the actual occupations, we have disaggregated human capital into three non-overlapping categories of *creative graduates*, *bohemians* and *non creative graduates*.

It is worth remarking that it goes beyond the scope of our contribution a detailed assessment on which occupations are really creative and whether 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. Moreover, one of the main advantages of the re-classification we are proposing is that it makes quite straightforward to check the robustness of the results by addressing specific occupations' misclassifications. For instance, if one is doubtful about the creativity content of an occupation such as that of Archivists and Librarians (ISCO 88 code 243), this subgroup of workers can be easily dropped from group A and included in the non-creative group. Similarly, if one believes that Managers (ISCO 88 codes 121 and 131) are creative, this profession can be excluded from group C and included in group A. In the robustness analysis presented in Section 6.2 we discuss this kind of potential misclassification in details.

Figure 1 shows the interconnections among the three human capital categories by reporting the European average shares with respect to population. We notice that employed graduates count for 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[5].

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 depicted 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 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 its 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.

[5] Our figures for the entire Europe are in line with those reported by Boschma and Fritsch (2009) for a subset of Nordic 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 highly skilled 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 cultural 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[6]. Some recent studies (Rodriguez-Pose and Crescenzi, 2008; Sterlacchini, 2008) have examined the effects of technological capital on the European regions performance offering general support to the positive 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 performing 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

[6] 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.

even more difficult since we need to measure it at the regional level for the whole Europe. Hence, as a proxy of cultural diversity we use the number of people living and working in any one of the 257 European regions, but born in a foreign country. In general, people born abroad bring diversified backgrounds in the new country of residence[7] and this facilitates the diffusion of new ideas, which, in turn, yields an increase in creativity and productivity for the whole economy[8]. 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. (2011) for the European regions.

Table 2 shows that the average value of foreign born population in Europe is 6.9% and it exhibits 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 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

[7] “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).

[8] 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.

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 to the advanced Western countries[9]. 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 to control 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 centres take value one, while the very densely populated regions with large centres, that are the urban areas, take the maximum value of six. In previous studies the territorial distribution of population turned out 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 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 variable 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

[9] 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.

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) located in each of the 257 European regions:

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

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. Since for the explanatory variables included in our empirical models it is not possible to exploit any kind of sectoral break-down, for consistency we impose inputs' elasticities to be the same across sectors. However, given the well-documented sectoral heterogeneity (Marrocu et al., 2010) we also considered a TFP measure derived by averaging individual TFP estimated by allowing the inputs' coefficients to change across sectors. The use of this alternative dependent variable is discussed in greater detail in the robustness analysis presented in section 7.

Turning to our basic measure of TFP, the comparison of the estimated values across the European regions (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, 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. Model specification 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:

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

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.[10] 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

[10] 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 and 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.

additional indication that there is no positive selection of graduate people into high-productive regions[11].

Model (2) was initially estimated by OLS and the spatial Robust LM tests[12], 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[13]. The tests provide evidence of spatially correlated residuals[14], 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:

$$\varepsilon_i = \rho W \varepsilon_i + u_i \qquad (3)$$

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

6. Assessing the role of human capital

In this section we discuss the results on the basic model and the robustness analysis performed to guard against potential misclassification problems due to the assumptions made to derive the three new proposed categories of human capital.

6.1 Basic results

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

[11] The same kind of results were obtained when we carried out the subsample analysis by dividing the whole sample into the 33%-67% or 25%-75% top-bottom performing regions.
[12] For a comprehensive description of spatial models and related specifications, estimation and testing issues refer to Le Sage and Pace (2009) and references therein.
[13] Such normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied.
[14] For the preferred specification (model 4, table 4), the robust LM error test is highly significant with a p-value of 0.001, while the robust LM lag test was significant only at a level of 0.054. Some robustness checks on the spatial pattern specification are postponed to section 7.

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 the estimates are biased due 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. 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 if measurement matters concerning the disaggregation of human capital are overlooked and this, in turn, does not provide reliable evidence for sound policy recommendations on the economic role played by its creativity and formal education components.

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.

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[15], 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 formation of

[15] Note that the model estimated by OLS returned quite similar elasticities: 0.17 for creative graduates, 0.05 for non creative graduates and -0.02 (not significant) for bohemians. Note also that most of the VIFs for the variables included in model (4) are well below 3 (only the technological capital has a higher VIF value, 4.8, which being less than 6 does not represent an issue); more specifically, for human capital variables they are: 2.2 for creative graduates, 1.4 for non creative graduates and 2.1 for bohemians.

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)[16].

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. Similar evidence was found by Nathan (2007) and Nathan and Lee (2011) for the case of UK firms and cities[17].

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., 2011, Florida et al., 2008, Wedemeier, 2010).

Turning to the other local economy control variables, 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 most advanced Western economies, as we have remarked in section 3. A possible explanation for this result is that 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 densely populated regions are

[16] 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).

[17] Comunian et al. (2010), following a different perspective of analysis, show that a significant mismatch is present in the UK labour market between creative occupations and bohemian graduates, who, despite their oft-claimed role in driving economic growth are at a salary disadvantage when compared to non-bohemian graduates. This finding casts further doubts on the economic relevance of the bohemian group.

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.

6.2 Robustness analysis on human capital classifications

In this section we discuss the empirical analysis carried out to assess the robustness of the results reported in table 4 with respect to some specific misclassification issues.

It could be claimed that the result on the negligible role played by Bohemians' 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, reported in the first column of table 5, are very robust to this variation in the classification and confirm the evidence previously presented for the preferred model specification[19].

In the second regression we assess whether the creative graduates coefficient might be affected by the inclusion of the professionals employed in the Archivists and Librarian group of occupations (ISCO 88 code 243), who are deemed to have one of the lowest creativity content with respect to the other occupations included in group A. They are therefore dropped from the creative graduates group and included in the non creative graduates one.

The opposite misclassification problem is addressed in the third regression, where we check whether the same coefficient could be biased due to the fact that we are excluding from the group of

[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%.

[19] We have also experimented with different proportions of misclassification error (in the range 10-30%) and model (4) results were extremely robust.

creative graduates the subgroups of directors and general managers (ISCO 88 codes 121 and 131), who can be expected to perform creative tasks in managing firms or in proposing innovative organizational solutions. These are therefore moved from the non creative to the creative graduates group.

The estimated coefficient of the creative graduates is pretty robust, it slightly decreases to a point estimate of 0.14 and remains highly significant in both regression 2 and 3 of table 5. On the contrary, the coefficient of the non creative graduates is drastically reduced to an estimate of 0.008 when directors and general managers are no longer included. This result is clearly driven by the fact that on average they account for around 4.5% of the non creative graduates population. Moreover, it highlights how low is the contribution to productivity enhancement of the remaining occupations (just 2.7% of the initial non creative graduates group), mainly represented by legislators, senior government official, legal and business professionals.

Finally, in the last regression of table 5 we checked for a possible interactive effect between creative graduates and technology capital; as it is well known innovation activity requires the presence of highly skilled people and at the same time such people is attracted by highly innovative regions. Although it is therefore reasonable to expect an additional effect on productivity, the positive interactive term does not turn out to be significant at conventional levels; note, however, that the creative graduates and technological capital individual coefficients are higher with respect to all the other specifications.

The empirical results provided by both the basic model and the alternative specifications, which allow to check for potential errors in the identification of the three non-overlapping categories of human capital, represent robust evidence on the productivity enhancing role played by traditional education measures and in unveiling the additional contribution of creativity. Thus, for a large sample of regions covering the whole European Union, it appears that both Glaeser's claim on education and Florida's intuition on creativity are consistent. Indeed creativity can unfold its effects only when high levels of formal education are present, while its economic relevance *per se* seems scarce.

7. Robustness analysis on model specification and control variables

In this section we discuss the results on the robustness checks performed to assess whether the previously discussed findings are dependent on the chosen model specification or are affected by the inclusion of alternative variables to proxy the institutional and territorial features of the regional economic environment.

7.1 Alternative model specifications

In the first two columns of table 6 we consider alternative ways to deal with the spatial dependence present in the data with respect to the basic model (regression 4 table 4), which entails a spatial error specification with the inverse distance spatial weight matrix. The first regression reports the results for the spatial lag model. Due to the presence of spatial spillovers[20], the coefficients point estimates cannot be compared with the ones reported in tables 4 and 5, but the estimated total effects (0.17 for creative graduates, 0.05 for non creative graduates and a not significant -0.03 for bohemians) are very much similar to the ones obtained from the basic specification. However, the negative sign and the marginal significance of the spatially lagged term signals that the spatial autoregressive model is outperformed by the spatial error one in capturing the geographical dependence across regions.

As a further check, we re-estimate the basic model by adopting an alternative spatial weight matrix, the contiguity one. The results are qualitatively similar to the basic model ones, both for the human capital indicators and for the control variables. It is worth noticing that the creative graduate elasticity is lowered to 0.11 and that of non creative graduates to 0.03, while the bohemians keep exhibiting a non significant effect; the estimated spatial error correlation coefficient (0.66) points out a diminished strength of the spatial association among regions; this result is reasonably due to the fact that the contiguity matrix is less accurate in capturing the regional connectivity structure when compared to the inverse distance one.

The last two regressions enable us to assess the robustness of human capital effects when a different way of computing the dependent variable is considered. In the first case (model 3), in order to smooth away undue business cycle effects, rather than using the 2007 TFP level, we calculate the five-year average over the period 2003-2007. To account for the high sectoral heterogeneity which characterizes inputs' elasticities, we also compute the 2007 TFP level for each region as the weighted average of 13 sectoral TFP levels obtained using inputs' elasticity estimated without imposing homogeneity restrictions across sectors.

According to the results of both specifications 3 and 4 the evidence provided by our basic model turns out to be pretty robust, with the creative graduates outperforming the non creative ones and with the bohemians still having no predictive power.

[20] In the lag model given the presence of the spatially lagged term the interpretation of the estimated coefficients as partial derivates with respect to a specific regressor no longer holds due to the fact that each region is neighbour to its neighbours so that affecting them it will receive, in turn, feedback effects. The change in the dependent variable caused by a unit change in one given explanatory variable amounts to the *total* effect, which is given by the sum of the *direct* effect, due to the change in a region's own regressor, and the *indirect* or spillover effect, caused by the series of feedbacks (Le Sage and Pace, 2009).

Therefore, we can confidently exclude that the diversified effects of human capital indicators previously discussed could have been driven by the specific way in which we computed our preferred regional measure of economic performance or by the way we account for spatial dependence.

7.2 Alternative control variables

Table 7 reports the results for the final array of robustness checks performed to assess whether the results may be, at least partially, driven by the specific set of control variables selected. Overall, the impacts of human capital variables are quite robust across the five different models considered and pretty much in line with those provided for the basic model, even if there is some evidence of slight variability.

As anticipated in section 5 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 raise some endogeneity concerns due to reverse causality as foreign people may be attracted by performing regions. To check for this we re-estimate our preferred basic specification 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)[21]. The estimated coefficient (first model of table 7), 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 another country does not seem to alter in a remarkable way the estimates for the whole sample[22]. 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 foreign people as neighbours. This new control is included in regression 2 of table 7, 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 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.

[21] No data on foreign population is available for Malta, Belgian, German and Greek regions.
[22] Note also that the approach suggested in Ottaviano and Peri (2006) and Bellini et al. (2011), 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.

Considering the other regional controls, we checked whether the specialization pattern is better represented by including the specialization index for knowledge intensive sectors rather than the one for manufacturing, which turned out to have an adverse effect on productivity according to the basic model results. As efficiency gains might be expected for economies specialized in the most innovative sectors, in the third model of table 7 we test this conjecture by including the corresponding specialization index. Although the coefficient sign is now positive, it is significant only at the 17% level. As already mention in section 6, industry specialization indices are outperformed by the settlement structure indicator, which, accounting for both population density and the presence of large centres, turns out to be superior also with respect to the simple population density variable (model 4).

Finally we also checked for possible influences of first nature geography factors by including a climate variable proxied by the yearly average temperature; as expected, we found a negative and significant effect, ceteris paribus regions with higher temperature are less productive. The creative graduate and non creative graduate variable remain positive and significant with slightly lower elasticities, 0.12 and 0.03 respectively, when compared to the basic model 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 creativity - 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 no direct economic role is found for the bohemians' component across all the different estimated specifications.

8. 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.

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 as a driver of regional development.

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 lack of a clear definition of what creativity actually entails and to what extent it differs from traditional human capital measures has lead to a wide array of particular classifications, crucially dependent on the aim of the specific empirical analysis they were included in. Although often acknowledged, the problem of the relevant overlapping between the concepts of education and creativity has not been consistently addressed, so that the evidence provided so far on their individual effects is not robust to the presence of multicollinearity or, even worse, omitted variable problems.

In this paper we propose a disaggregation of human capital into three non-overlapping categories in order to overcome such a 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 allowing us to provide reliable and sound evidence on their impacts on regional productivity. 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 graduates group, which exhibits an effect of approximately 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 an extensive set of robustness checks, including possible misclassification issues in our grouping approach, 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 and offers a sound base to reconcile the up-to-now opposite views of Glaeser's supporters on one side and Florida's fans on the other.

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.

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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 centres, 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
Climate	TEMP	Annual average temperature	ESPON 2013 program
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, 2007

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. Robustness analysis on human capital variables

Dependent variable: total factor productivity, 2007
Spatial error models

	1	2	3	4
Checking for misclassification of:	Bohemians (a)	Archivists Librarians (b)	Directors Managers (c)	
Human capital				
Creative graduates	0.167 ***	0.146 ***	0.140 ***	0.199 ***
	(0.052)	(0.052)	*(0.053)*	*(0.072)*
Non creative graduates	0.043 ***	0.047 **	0.008 ***	0.039 **
	(0.016)	(0.022)	*(0.003)*	*(0.017)*
Bohemians	-0.031	-0.029	-0.021	-0.029
	(0.025)	(0.024)	*(0.024)*	*(0.024)*
Creative graduates*Tech. Capital				0.013
				(0.018)
Control variables				
Technological capital	0.068 ***	0.069 ***	0.076 ***	0.108 **
	(0.013)	(0.013)	*(0.013)*	*(0.056)*
Diversity	0.056 ***	0.057 ***	0.056 ***	*0.059* ***
	(0.014)	(0.014)	*(0.014)*	*(0.014)*
Manufacture specialization	-0.238 ***	-0.244 ***	-0.243 ***	-0.232 ***
	(0.072)	(0.072)	*(0.074)*	*(0.072)*
Settlement structure	0.021 **	0.022 ***	0.024 ***	0.021 **
	(0.009)	(0.009)	*(0.008)*	*(0.009)*
Dummy 4 largest countries	0.151 ***	0.149 ***	0.143 ***	0.154 ***
	(0.033)	*(0.034)*	*(0.034)*	*(0.033)*
Dummy convergence regions	-0.227 ***	-0.224 ***	-0.202 ***	-0.226 ***
	(0.042)	(0.043)	*(0.044)*	*(0.042)*
Spatial error correlation coefficient	0.893 ***	0.895 ***	0.897 ***	0.896 ***
	(0.075)	*(0.074)*	*(0.072)*	*(0.073)*
Square corr., actual and fitted values	0.814	0.817	0.815	0.818

(a) The creative graduates variable is increased by an amount equal to 20% of the bohemians variable, the latter is reduced accordingly; see section 6.2 for details.

(b) Archivists, librarians and related information professionals (ISCO 88 code 243) are dropped from the creative graduates group and included in the non creative graduates one.

(c) Directors and chief excutives (ISCO 88 code 121) and General managers (ISCO 88 code 131) are dropped from the non creative graduates group and included in the creative gradutes one.

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 6. Robustness analysis on the spatial specification and on the TFP dependent variable

Dependent variable: total factor productivity, 2007
Spatial error models

	1		2		3		4	
	Lag model (a)		Spatial weight matrix contiguity		TFP 2003-2007 average		TFP 2007 sectorial elasticities	
Human capital								
Creative graduates	0.178	***	0.114	**	0.150	***	0.119	**
	(0.051)		*(0.050)*		*(0.050)*		*(0.053)*	
Non creative graduates	0.052	***	0.027	*	0.039	**	0.046	***
	(0.016)		*(0.015)*		*(0.016)*		*(0.017)*	
Bohemians	-0.029		0.004		-0.038		-0.004	
	(0.024)		*(0.024)*		*(0.024)*		*(0.025)*	
Control variables								
Technological capital	0.066	***	0.062	***	0.068	***	0.074	***
	(0.013)		*(0.012)*		*(0.013)*		*(0.013)*	
Diversity	*0.056*	***	0.069	***	0.067	***	0.059	***
	(0.013)		*(0.015)*		*(0.013)*		*(0.014)*	
Manufacture specialization	-0.251	***	-0.191	***	-0.256	***	-0.816	***
	(0.070)		*(0.073)*		*(0.071)*		*(0.075)*	
Settlement structure	0.022	**	0.020	***	0.022	***	0.015	*
	(0.009)		*(0.008)*		*(0.008)*		*(0.009)*	
Dummy 4 largest countries	0.170	***	0.173	***	*0.141*	***	0.212	***
	(0.029)		*(0.037)*		*(0.033)*		*(0.034)*	
Dummy convergence regions	-0.232	***	-0.195	***	-0.242	***	-0.305	***
	(0.042)		*(0.040)*		*(0.042)*		*(0.044)*	
Spatial lag coefficient	*-0.043*	*						
	(0.022)							
Spatial error correlation coefficient			0.655	***	0.916	***	0.818	***
			(0.077)		*(0.059)*		*(0.125)*	
Square corr., actual and fitted values			0.848		0.828		0.876	

Note : when not differently indicated, the model specification is the spatial error one, the dependent variable is the 2007 TFP variable calculated by applying common sectoral input elasticities and the spatial weight matrix is the inverse distance matrix, max-eigenvalue normalized.

Estimation method: ML. Obervations: 257 regions. All regressions include a constant term.

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

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

(a) We do not report the estimated direct, indirect and total effects, but they are available upon request.

Table 7. Robustness analysis on control variables

Dependent variable: total factor productivity, 2007
Spatial error models

	1	2	3	4	5
Human capital					
Creative graduates	0.156 ***	0.159 ***	0.158 ***	0.180 ***	0.119 **
	(0.058)	*(0.051)*	*(0.053)*	*(0.051)*	*(0.051)*
Non creative graduates	0.030 *	0.041 **	0.045 ***	0.042 ***	0.032 **
	(0.018)	*(0.016)*	*(0.017)*	*(0.016)*	*(0.016)*
Bohemians	-0.025	-0.026	-0.019	-0.022	-0.037
	(0.028)	*(0.024)*	*(0.025)*	*(0.025)*	*(0.024)*
Control variables					
Technological capital	0.082 ***	0.068 ***	0.052 ***	0.068 ***	0.058 ***
	(0.015)	*(0.013)*	*(0.012)*	*(0.013)*	*(0.013)*
Diversity		0.056 ***	0.068 ***	0.054 ***	0.076 ***
		(0.014)	*(0.013)*	*(0.014)*	*(0.015)*
Diversity 2001	0.076 ***				
	(0.022)				
Tolerance		0.048			
		(0.099)			
Manufacture specialization	-0.172 *	-0.239 ***		-0.230 ***	-0.282 ***
	(0.091)	*(0.072)*		*(0.072)*	*(0.071)*
Knowledge specialization			0.185		
			(0.136)		
Settlement structure	0.020 **	0.021 **	0.015 *		0.031 ***
	(0.010)	*(0.009)*	*(0.009)*		*(0.009)*
Population density				0.016	
				(0.013)	
Climate					-0.019 ***
					(0.006)
Dummy 4 largest countries	0.181 ***	0.150 ***	0.155 ***	0.163 ***	0.155 ***
	(0.044)	*(0.033)*	*(0.035)*	*(0.033)*	*(0.033)*
Dummy convergence regions	-0.263 ***	-0.224 ***	-0.232 ***	-0.227 ***	-0.226 ***
	(0.056)	*(0.043)*	*(0.043)*	*(0.043)*	*(0.041)*
Spatial error correlation coefficient	0.896 ***	0.893 ***	0.917 ***	0.885 ***	0.904 ***
	(0.073)	*(0.075)*	*(0.058)*	*(0.080)*	*(0.067)*
Square corr., actual and fitted values	0.826	0.814	0.805	0.811	0.826
Observation	193 (a)	257	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) Data on Malta, Belgian, German and Greek regions are not available.