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 that human capital plays in economic performances. The standard way to measure the human capital endowment is to consider the educational attainments of the resident population, usually the share of people with a university degree. 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, the arts, culture, and entertainment. However, the empirical analyses conducted so far have overlooked a serious measurement problem concerning the clear definition of the education and creativity components of human capital. This article aims to disentangle this issue by proposing a disaggregation of human capital into three nonoverlapping categories: creative graduates, bohemians, and noncreative 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, noncreative graduates exhibit a lower impact, and bohemians do not show a significant effect on regional performance. Moreover, a significant influence is exerted by technological capital, cultural diversity, and industrial and geographic characteristics, thus providing robust evidence that a highly educated, innovative, open, and culturally diverse environment is becoming more central for productivity enhancements.

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There is a wide and long-standing consensus among economists and social scientists on the key role played by human capital in influencing levels of productivity and growth (Lucas 1988). The availability of skilled and highly educated people in a specific area can be seen as the primary determinant of local economic performance, since other important factors, like the creation of new ideas and technological innovation, are strongly reliant on the human capital endowment. 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 localization process is self-reinforcing, and therefore firms' and local productivity are enhanced (Jacobs 1969). This virtuous mechanism tends to accentuate the regional polarization pattern, given the existence of localized 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 of human capital is educational success, usually measured by the share of the population who attained at least a university degree. However, this proxy has been recently criticized on the grounds that it is not fully adequate to capture the real capabilities of each individual, since these capabilities are based not only on schooling, but also on personal skills—like creativity and innovativeness—and on accumulated experience.

Florida (2002) suggested that what people really do is more important than what is stated in their formal educational attainments. More specifically, he proposed focusing on the level of creativity in the local economy, measured by the share of the population who are employed in occupations like the sciences, engineering, education, culture, the arts, and entertainment.[1] Creative people are workers whose economic function is to identify problems and to find original solutions by generating new ideas, creating new technology, or combining existing knowledge in new and innovative ways. Since Florida's book was published, the influence of the creative class on urban

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

and regional performances has been tested in several contributions applied to different geographic contexts. The European Commission (EC 2009) declared 2009 the year of creativity, highlighting the potential impact of creativity on regional economic performance.

However, the definition of creative class suggested by Florida has been criticized for being too broad to enable a practical operationalization of this concept in empirical models assessing the role of creativity as an engine of economic development. In applied contributions, several attempts have been made to reach a workable concept of creativity, but since the concept is heavily dependent on the specific aim of the study that uses it, these attempts have made the overall picture even more blurred.

An even more serious critique is that the concept of the creative class overlaps so much with the concept of human capital that it is difficult to gain a clear understanding of the relationships between creativity and education and their effects on regional economic growth (Glaeser 2005). The view that creativity exerts an independent positive role on local performance has been strongly criticized on the ground that the set of individuals occupied in creative jobs strongly overlaps with the number of individuals with tertiary degrees. In a critical review of Florida's contribution, Glaeser showed that if an indicator of schooling (the population with bachelor's degrees) is added as an explanatory variable of population growth in U.S. metropolitan areas, then all the creative variables become irrelevant. This finding proves that once one controls for the traditional measure of human capital—schooling—there is no role left for bohemians and other creative types to explain local economic performance. Although Florida (2002) claimed that creative potential is by no means dependent on having acquired a high level of formal education, in his most recent study, he acknowledged Glaeser's critique and accepted the idea that they are somehow complementary in driving regional development (Florida, Mellander, and Stolarick 2008).

Overall, the controversy over how to measure human capital (education or creativity) and which of the two elements plays a major role is still ongoing. The key issue is the strong overlap between graduates and creatives, and this problem, although acknowledged in the literature, has continued to be overlooked in empirical applications. Most of the individuals who are included in the creative class are indeed graduates, so it is difficult to disentangle which effects on local performances are due to their creativeness and which to their education. In the econometric analyses, the unclear identification of the education and creativity components generates a measurement problem, leading to confusing evidence because the human capital effects are inadequately estimated, owing to either multicollinearity problems or to omitted variable bias. Therefore, a clear definition of the various categories of education and creativity is needed to attain a more accurate evaluation of their impacts.

The main purpose of this article is to provide an empirical contribution to the literature by proposing a strategy to distinguish the various components of human capital. In our study, we disaggregate human capital into three nonoverlapping categories: *creative graduates*, *bohemians,* and *noncreative graduates*. We identified these categories by combining the information on educational attainments with that related to actual occupations, in an attempt to account simultaneously for both potential skills and those applied on the job. Thus, if creativity is really making formal education more economically valuable, it should show up as an additional effect for creative workers over and above the one associated with traditional human capital measures, thus reconciling Florida's (2002) and Glaeser's (2005) "opposite" views.

In our empirical analysis, we assessed the concurrent effects of the human capital indicators on the economic efficiency of 257 regions belonging to the 27 member countries of the European Union (see Appendix 1 for a list of the regions). It is worth emphasizing that this is the first time that the concurrent effects of human capital—those that do and do not apply talent—has been analyzed 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 of debate in the literature. Some studies have used indirect indicators of outcomes, like the number of innovations or the presence of high-technology industries, whereas others have used final, although rough, measures of economic performance like employment growth. In our study, we used an estimated measure of total factor productivity (TFP) as an indicator for regional economic performance, which already accounts for the contribution of traditional production factors (capital and labor). TFP is thus robust to the structural change processes that have been taking place in all European economies over the past decades and that have significantly affected the dynamics of employment. Therefore, labor growth is not an adequate indicator of performance for assessing the role of human capital in determining economic outcomes.

A further important element of our analysis was the inclusion of other interrelated features of the local environment, such as the institutional setting, the production of knowledge, cultural diversity, and the productive structure, all of which contribute to drive the success of a regional economy, because they are often associated with the presence of highly skilled people in a specific area (Glaeser, Kolko, and Saiz 2001; Dettori, Marrocu, and Paci 2011). Assessing the role of education and creativity while controlling for external institutional and economic factors is particularly important in the European context, which is characterized by a high degree of regional heterogeneity (Asheim and Hansen 2009). Therefore, we tested 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 geographic characteristics), which are expected to interact with human capital in determining local productivity. Finally, since our observations refer to geographic regions, we adopted the specific estimation approach that enabled us to deal with the issue of spatial dependence between neighboring regions.

The article is organized as follows. In the next section, we discuss the various measures of human capital that have been used in the literature and suggest a way of defining three nonoverlapping categories. In the third section, we examine other characteristics of the regional environment that affect regional performance. In the fourth section, we present the estimation of the regional TFP, which is our preferred indicator of economic performance. In the fifth section, we present the empirical model and discuss some methodological issues. The econometric results for the basic model are presented in the sixth section along with some checks for robustness of the human capital indicators. The following sections present a wider analysis of robustness on model specification and on alternative control variables, followed by the conclusion. A complete definition of the variables and data sources is presented in Table A2 in the appendix.

Measures of Human Capital

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 educational attainment, which is expected to take us in the direction of overcoming the measurement problem discussed in the literature. Following Florida's (2002) contribution, the concept and measurement of the creative class received wide attention (Peck 2005; Villalba 2008). Given the initial broad and elusive definition of the creative class, most empirical studies first tackled the issue of what is meant by the creative class and then figured out their own specific definitions. For instance, McGranahan and Wojan (2007) emphasized that Florida's creative class includes not only occupations that require a high level of education but also some technical occupations that, over time, have acquired important decision-making responsibilities, and such a high level of aggregation may indeed lead to low "construct validity."[2] For this reason, they proposed a narrow definition of the creative class—the *recast* creative class—based mainly on the creativity content of occupations derived from the U.S. Occupational Information Network. Therefore, they dropped occupations that require "little creative thinking" and are more reproduction and execution oriented from the broad definition. Doing so enabled them to reduce the high heterogeneity within creative occupations, which could lead to misleading results in the empirical analysis (Comunian, Faggian, and Li 2010).

The impact of the creative class on regional performance has been analyzed in several contributions applied to various geographic contexts, from U.S. 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 such as the United Kingdom (Nathan 2007), Sweden (Mellander and Florida 2011), the Netherlands (Marlet and van Woerkens 2007), and Germany (Wedemeier 2010); to a group of northern European countries (Boschma and Fritsch 2009; Andersen, Hansen, Isaksen, and Raunio 2010).

It is difficult to propose a consistent interpretation of the findings of these studies, given the differences in the definitions of creative class, institutional settings, econometric methods, measures of regional performance, and 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. McGranahan and Wojan (2007) found similar results using a restrictive definition of creative occupations; they showed that creativity has an effect on the employment growth in rural U.S. counties that is independent of the endowment of people with graduate degrees. On the other hand, some studies have shown that the creative class hypothesis was not supported, as was the case for the U.K. cities (Nathan 2007). Contrasting results were also found by Boschma and Fritsch (2009): considering alternatively both proxies of human capital in a model of employment growth, they found that the creative class measures dominated the indicator of education in the Netherlands, whereas the opposite occurred in Germany. Moreover, in the analysis of four Nordic countries (Denmark, Finland, Norway, and Sweden) Andersen et al. (2010) showed that the positive role of the creative class in supporting economic development was confirmed only for the case of the large city regions, but results for the smallest areas did not show a similarly strong role. In other studies, the two measures of human capital seemed to play different but complementary roles. In a path model of a regional development system, Florida et al. (2008) found that the creative class influences labor productivity, while educational attainments affect regional income. Note, however, that in both Florida et al. and Mellander and Florida, great care was taken to account for differences among the various occupations, but the crucial issue of assessing the extent to which the effects of creativity were inflated by the concurrent presence of graduates was not addressed.

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

In our opinion, the key issue is that the significant overlapping between the two measures of human capital—education and creativity—may yield ambiguous empirical results. Indeed, the econometric 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 is considered). To tackle this problem, it is worth starting with a careful reconsideration of the various definitions of creativity, along the lines initially suggested by Florida (2002). As we mentioned in the introduction to this article, Florida's concept of creative class is broad and includes a wide range of occupations, from those characterized by the most innovative tasks to those that involve just mere executive duties. Moreover, it is difficult to reproduce Florida's classification exactly on the basis of U.S. statistics using data for other countries. Furthermore, in the literature, each contribution has used slightly different definitions of creative class, depending on the territorial coverage and thus on the data sources that were used.

In our study, we followed the classification of creative class that is based on the International Standard Classification of Occupations (ISCO 88), reported in the EC report (2009, 17) and available in the European Labour Force Survey (ELFS) for the 27 EU countries included in our sample.[3] This classification considers two groups—the "creative core" and "bohemians"—which have the highest creativity score because they include professionals such as architects, engineers, academics, and those with cultural and artistic occupations, among others. The EC classification is similar to the one used by Boschma and Fritsch (2009), but, unlike the latter, it does not include those "creative professionals" (legislators, business and legal professionals, and a great deal of technicians) whose tasks have a lower creativity content.

On the basis of the EC classification, we decomposed the category usually called the creative class into two main categories (see Table 1): (A) *creative graduates*, including those in scientific, life sciences, health, teaching, library and social sciences professional occupations (this group corresponds to the one usually referred to as the "super creative core" or the "creative core" in the literature), and (B) the *bohemians*, consisting of artistic, entertainment, and fashion professionals.

The point we want to stress is that the occupations listed in Table 1A belong to the Major group 2, Professionals of the ISCO classification and require the tertiary level of education. It is obvious, for instance, that to become a physicist, an architect, a physician, or even an economist, one needs at least a tertiary degree.[4] This is why it is misleading to label this group the "creative core," as is done in the literature, since these individuals are, at the same time, *university degree* holders working in *creative* occupations. It is really difficult to claim that the creative aspect is more important than the educational one in the case of, say, a physician 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

[3] Ideally, we would need individual data that were disaggregated by three-digit ISCO occupations, by educational attainment, and by NUTS2 regions. However, such detailed information is not available because of anonymization procedures, which is why individual data, like the ELFS or the European Community Household Panel, are often transformed into macrodata at the regional level (Rodríguez-Pose and Vilalta-Bufí 2005). Contributions based on micro individual data were recently proposed only with regard to some specific countries: Comunian et al. (2010) for the United Kingdom; Mellander (2008) for Sweden, and King et al. (2010) for the United States, Canada, and Sweden.

[4] There may be few exceptions. For example, in the case of 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.

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 preprimary 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. Noncreative graduates *(nonexhaustive list)*	
111	Legislators
112	Senior governmental 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 as:	
3	Technicians and associate professionals

Source: International Standard Classification of Occupations (ISCO 88).

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 is usually labeled *bohemians* and includes those in several creative occupations like writers, painters, musicians, dancers, actors, designers, acrobats, and athletes. For this group, it is more complicated to discern the individual educational attainment just by looking at the list of occupations. For instance, in the field of music, most classical musicians and directors are expected to have a tertiary level of education, while rock musicians, most likely, do not have university degrees. Unfortunately, it is not possible to have direct information on the educational attainment of these individuals. Therefore, we made the most unfavorable hypothesis with respect to our purpose—to assess the specific contribution of the creative component on local performance—and assumed that all bohemians are just creative and are not university graduates. Therefore, we presumed that in these occupations, the creative component is 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 or his educational level. We are aware that with such a hypothesis, we are most likely inducing another kind of measurement error, since at least a certain number of bohemians have university degrees and should be added to the creative graduates group. In the econometric analysis, we test whether such a possible measurement error affects our results.

The other type of data available to measure the regional endowment of human capital is educational attainment. The influence of education has been well documented in nationwide studies (Mankiw, Romer, and Weil 1992; Benhabib and Spiegel 1994) and at the regional level (see, among many others, Rauch 1993 for the United States; Di Liberto 2008 for Italy; and Ramos, Suriñach, and Artís 2010 for Spain). Moreover, this issue is becoming even more relevant, since the differences in human capital endowments are increasing at the regional level because of local agglomeration effects (Berry and Glaeser 2005).

Following a well-established literature, we proxied human capital by graduates, that is, the number of employed people who have attained at least a university degree (ISCED 5–6). For this group, no detailed information is available on their actual occupations. But, as we have already stressed, a significant part of them are already counted within the creative graduates category described earlier. Thus, it is not correct to include both categories in the econometric analysis, since doing so 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 with university degrees; to do so, we introduce a new category: (C) *noncreative graduates*, computed as the difference between the total number of employed graduates and the creative graduates.

In Table 1C we report the most likely occupations of the noncreative graduates, who include legislators, governmental officials, managers, business professionals, and legal professionals. This list is not exhaustive, since a graduate may work as a farmer or a clerk, but this possibility does not affect our procedure, which aims to set this category apart from the creative groups. Some of these occupations (legislators, senior officials and managers, business professionals, and legal professionals) are sometimes included in the category creative professionals (Florida et al. 2008; Boschma and Fritsch 2009). Again, it is disputable whether 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 would only widen the overlap between the creative and educational components and introduce 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 disaggregated human capital into the three nonoverlapping categories of *creative graduates*, *bohemians* and *noncreative graduates*.

It is worth remarking that making a detailed assessment of which occupations are really creative and whether they should be included among the various groups of creatives goes beyond the scope of our contribution (for a critical view, see Markusen 2006; McGranahan and Wojan 2007). Our interest is 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 reclassification we are proposing is that it makes it straightforward to test 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 noncreative 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 later 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. It shows that employed graduates count for 12.5 percent of the population and that among them, the noncreative graduates are the major component (7.2 percent), while the creative graduates are 5.3 percent. On the other hand, the average share of the creative class in Europe is equal to 5.9

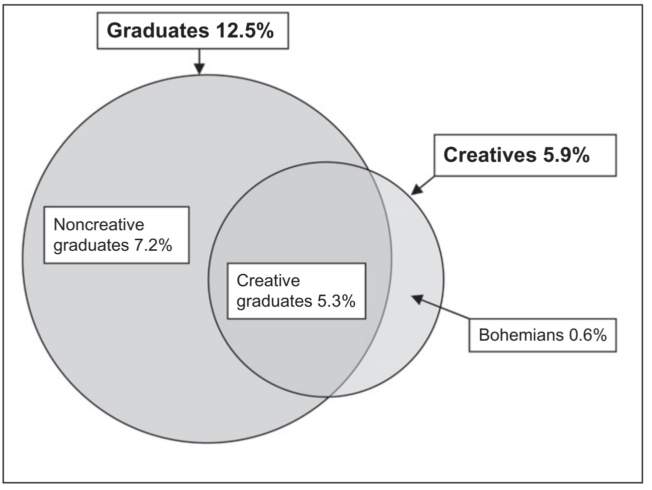

Figure 1. Graduates and creatives (percentage of the population aged 25 and older).

percent of the population, and the great majority of them are creative graduates (5.3 percent), while only 0.6 percent are bohemians.[5] We believe that the identification of the 3 nonoverlapping groups of noncreative graduates, creative graduates, and bohemians, based on their occupational contents, provides an operational 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 geographic distribution of the creative graduates is depicted in Figure 2, which shows that the presence of highly educated and creative people follows a well-defined spatial pattern with the highest values recorded for the Scandinavian, Baltic, and northern countries (Germany, the 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, one sees 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, and Amsterdam) and other regions, close to the capital city, which host universities renowned worldwide (Utrecht, Oxford, and Louvain-la-Neuve).

The second component of the human capital endowment is the bohemian group, which represents a small share of the population (0.6 percent for the European average), since it includes only the strictly creative occupations listed earlier. The most "bohemian" region is Inner London (4.4 percent of the population), followed by the Amsterdam region (2.7 percent) and other city regions like Stockholm, Outer London, Hamburg, Prague, Berlin. Indeed, the spatial distribution of the bohemians (see Figure 3) appears more scattered, and its high spatial dispersion is 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 European countries.

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

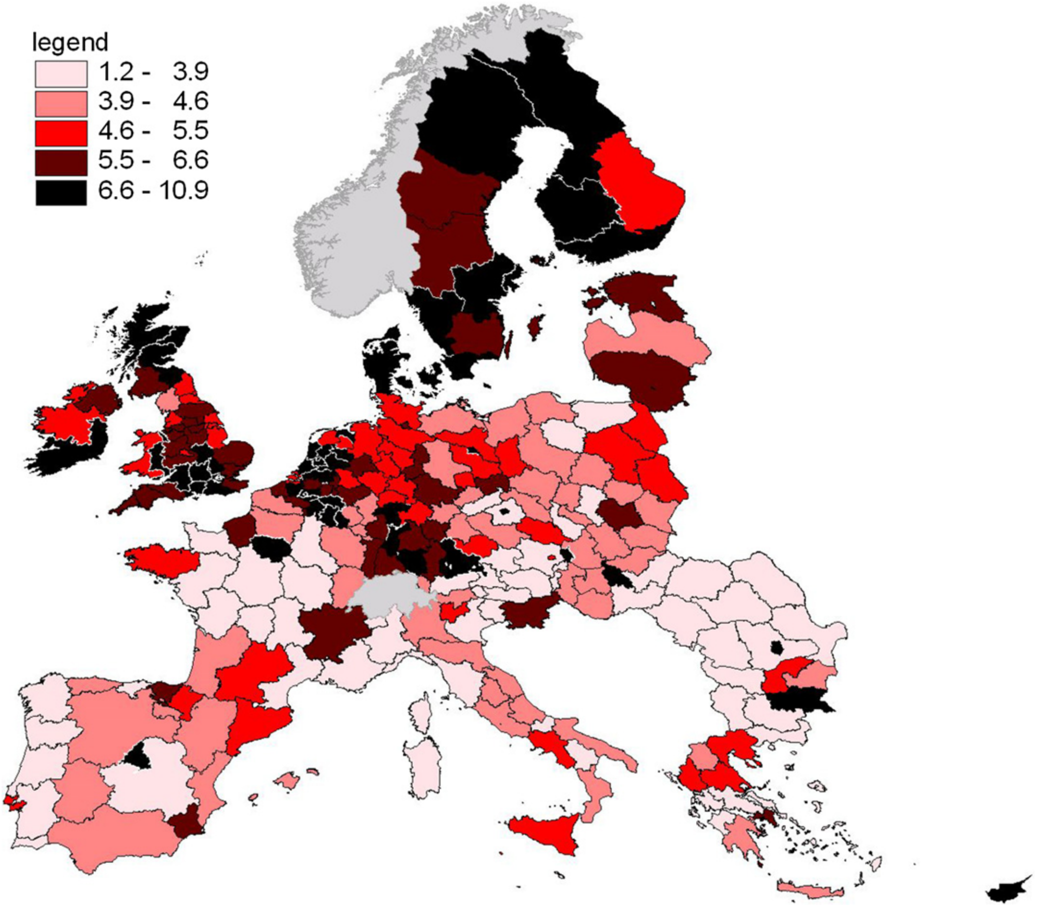

Figure 2. Creative graduates (employment of creative graduates in the population aged 25 and older, percentage, 2002).

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

Other Characteristics of the Regional Environment

The main goal of our study was to assess the influence of different measures of human capital on the efficiency levels of the European regions. Nonetheless, it was important to control for other variables that 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 included several additional factors that are perceived as increasingly relevant in shaping the local environment: technological capital, the level of cultural diversity and tolerance, and industrial and geographic characteristics.

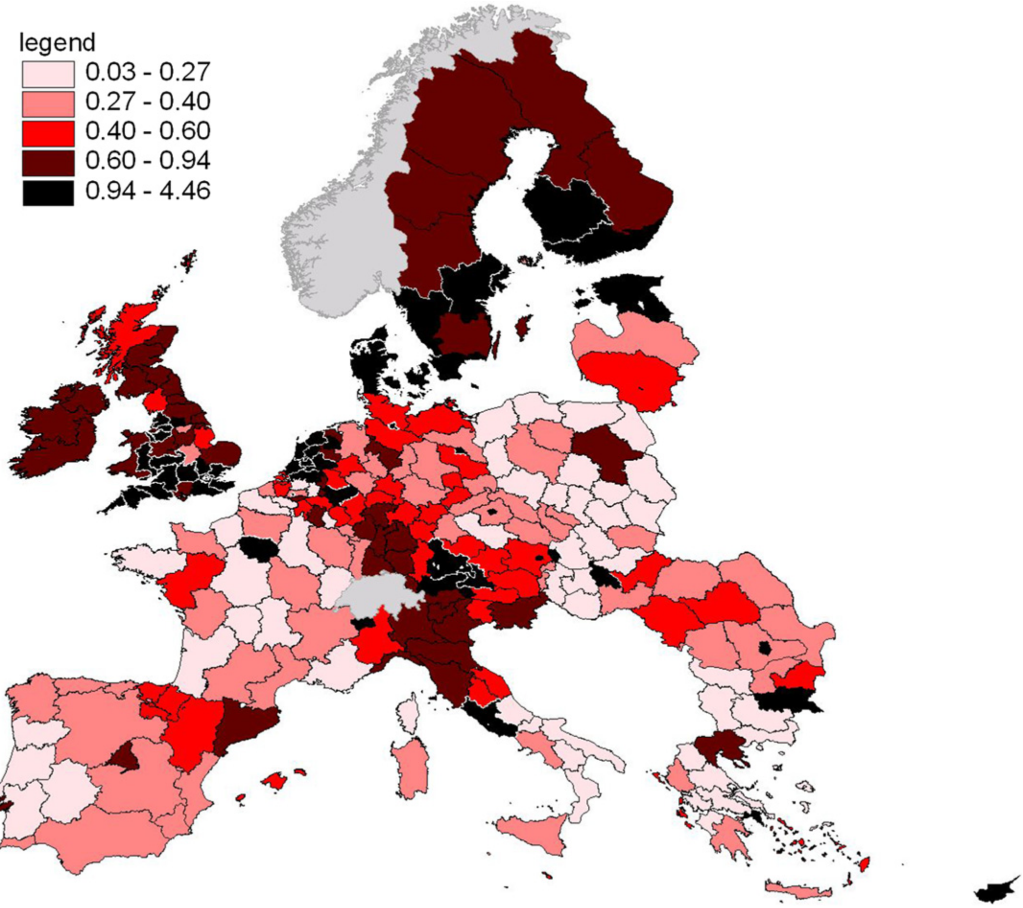

Figure 3. Bohemians (employment of creative bohemians in the population aged 25 and older, percentage, 2002).

The first factor is technological capital, which represents a significant aspect of the intangible assets that are essential to enhance the productivity of the local economy. The impact of a direct measure of technological stock on output level was originally suggested by Griliches (1979) in the so-called knowledge-capital model and afterward was used in several contributions at the enterprise, region, and country levels. 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, which, in turn, enhances regional performance.[6] Some recent studies (Rodríguez-Pose and Crescenzi 2008; Sterlacchini 2008) have examined the effects of technological capital on the European regions' performance, offering general support for the positive role exerted by the innovation variables on economic outcomes. In our study, we used the stock of patents granted by the European Patent Office (EPO) from 2000 to 2004 divided by the total population as an indicator of technological capital. The data were regionalized on the basis of the inventors' residence; in the case of patents with multiple inventors, proportional quotas were

[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 economic performance.

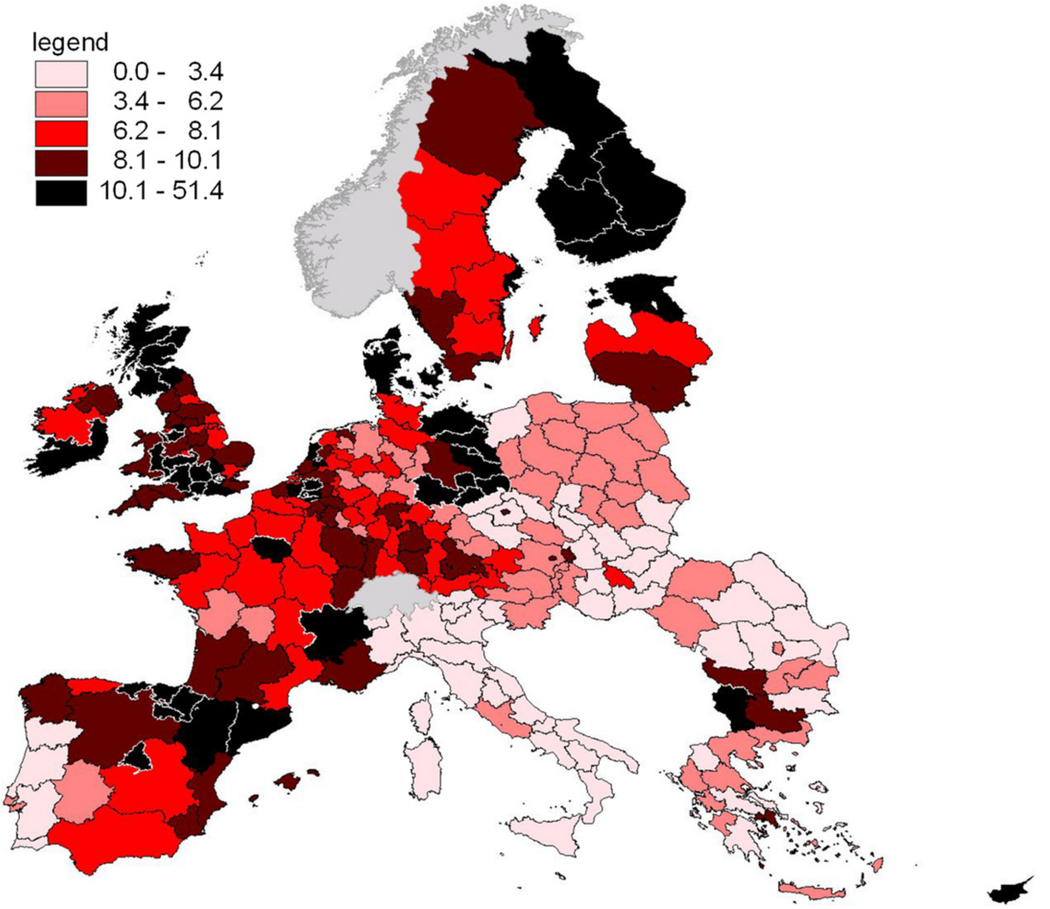

Figure 4. Noncreative graduates (employment of noncreative graduates minus creative graduates in the population aged 25 and older, percentage, 2002).

attributed to each region. The geographic distribution of technological capital across the European regions is represented in Figure 5. It shows a clear pattern of spatial concentration also indicated 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, signaling the presence of a Scandinavian cluster. On the other hand, all southern and eastern European regions are characterized by low levels of technological capital.

The second variable is the degree of cultural diversity in the region, which is supposed to favor local performance, since it signals a region's capacity to attract people from outside. It is not an easy task to find an appropriate measure for a multifaceted factor such as diversity, and this task was even more difficult because we needed to measure it at the regional level for the whole of Europe. Hence, as a proxy for cultural diversity, we used the number of people living and working in any one of the 257 European regions, but born in a foreign country. In general, people who were born abroad bring diversified

Table 2

Summary Statistics

Variable	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
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
Noncreative 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
Manufacturing specialization[d]	–0.59	0.35	–0.04	0.19	–4.75
Knowledge specialization[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 the population aged 25 and older
[b] per thousand of population
[c] % values over the population
[d] normalized index [–1, +1]

backgrounds to their new country of residence,[7] which facilitates the diffusion of new ideas that, in turn, result in an increase in creativity and productivity for the entire economy.[8] Moreover, migrants are usually younger and therefore more dynamic and open to new ideas and technologies. This measure was used by Ottaviano and Peri (2006) for U.S. cities and by Bellini, Ottaviano, Pinelli, and Prarolo (2011) for the European regions.

Table 2 shows that the average percentage of the foreign-born population in Europe is 6.9 percent, and this value exhibits high variability, from the minimum level of 0.01 percent in the Romanian region of Centru to the highest value of 37.6 percent in Inner London. It is interesting that the variability of this indicator across regions (CV = 0.83) is much higher than the human capital measures that we previously analyzed. 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 Balearic islands, Valencia, Catalonia, Provence, and Côte d'Azur. On the other hand, as expected, in most regions of eastern Europe (Romania, Bulgaria, Hungary, and Poland), the share of the foreign born population is low.

Strictly related to cultural diversity is the level of tolerance, which Florida (2002) suggested is one of the three Ts—talent, technology, and tolerance—that contributes to building a local environment that is favorable to economic performance. An open and tolerant society is able to accept a large share of the external population, to attract new ideas, and thus to enhance economic efficiency. As a measure of tolerance, we used the share of population that, in the European Value Studies (EVS) questionnaire, did not mention 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 tolerant (86.6 percent did not mention the item), although values below 50 percent were found in the

7 "Immigrants have complementary skills to natives not only because they perform different tasks, but also because they bring different skills to the same task" (Florida et al. 2008, 620).

8 For the case of London firms, Nathan and Lee (2011) provided evidence that firms that are diverse in terms of ownership, teams, or management are more innovative in developing new products and in implementing new processes. They also provided an exhaustive description of how the links between cultural diversity and innovativeness work at the individual, firm, and urban levels.

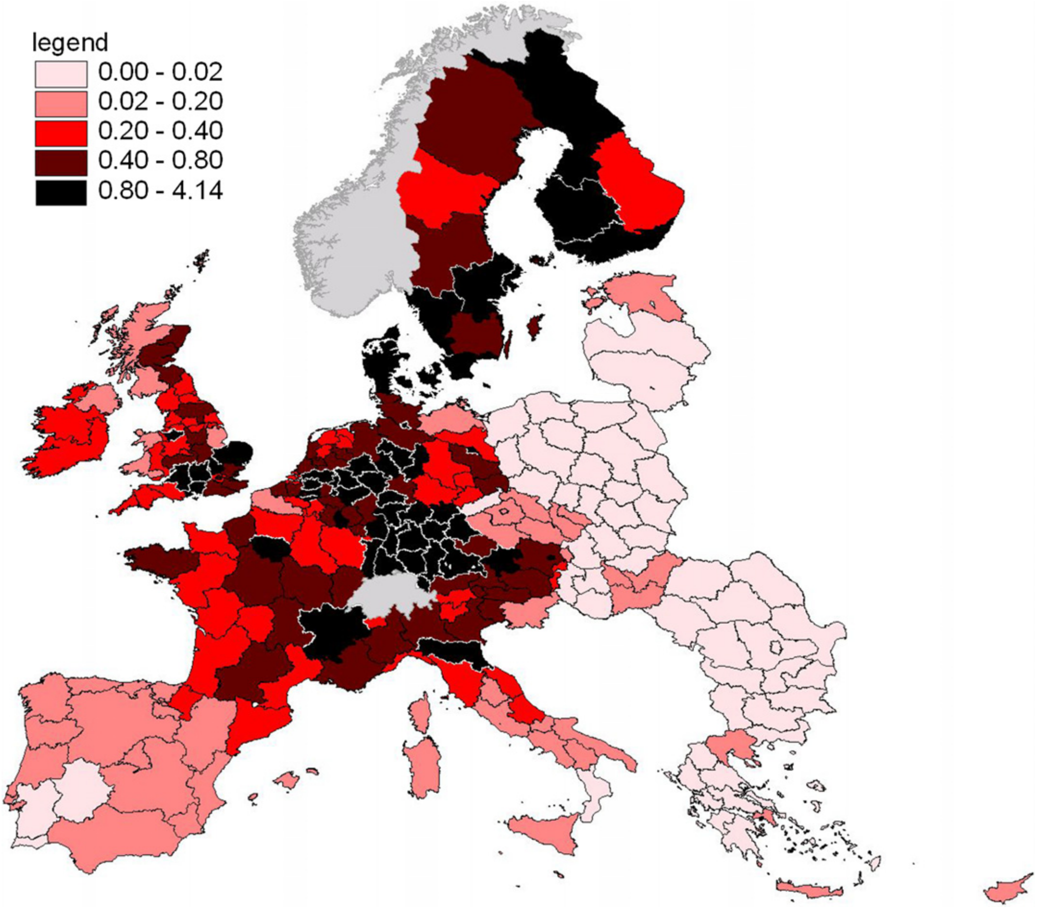

Figure 5. Technological capital (patents at EPO per thousand population, stock years 2000–4).

Austrian region of Kärnten (45 percent), in Severozapad (the Czech Republic, 48 percent) and Oberpfalz (Germany, 49 percent), indicating considerable levels of intolerance toward immigrants and the foreign population, which may be detrimental for economic performance (see Figure 7).

We also controlled for the production structure of the economy by including two alternative indicators of regional relative specialization in the manufacturing sectors and in the knowledge-intensive ones. It should be noted that during the period under study, the regions specializing in manufacturing were located mainly in the eastern European countries, while the knowledge-intensive regions were in the advanced western European countries.[9] This difference in productive specialization was expected to affect regional productivity (Marrocu, Paci, and Usai 2010).

Another important feature of the local environment is the regional structure of inhabited settlements, which allowed us to control for the role played by the agglomeration

[9] For manufacturing, the top 5 regions were in the Czech Republic, Hungary, and Romania and that among the top 10, there was only one German and one Italian region; in the knowledge-intensive sectors, the top 10 regions were in the United Kingdom, Luxembourg, the Netherlands, France, and Brussels.

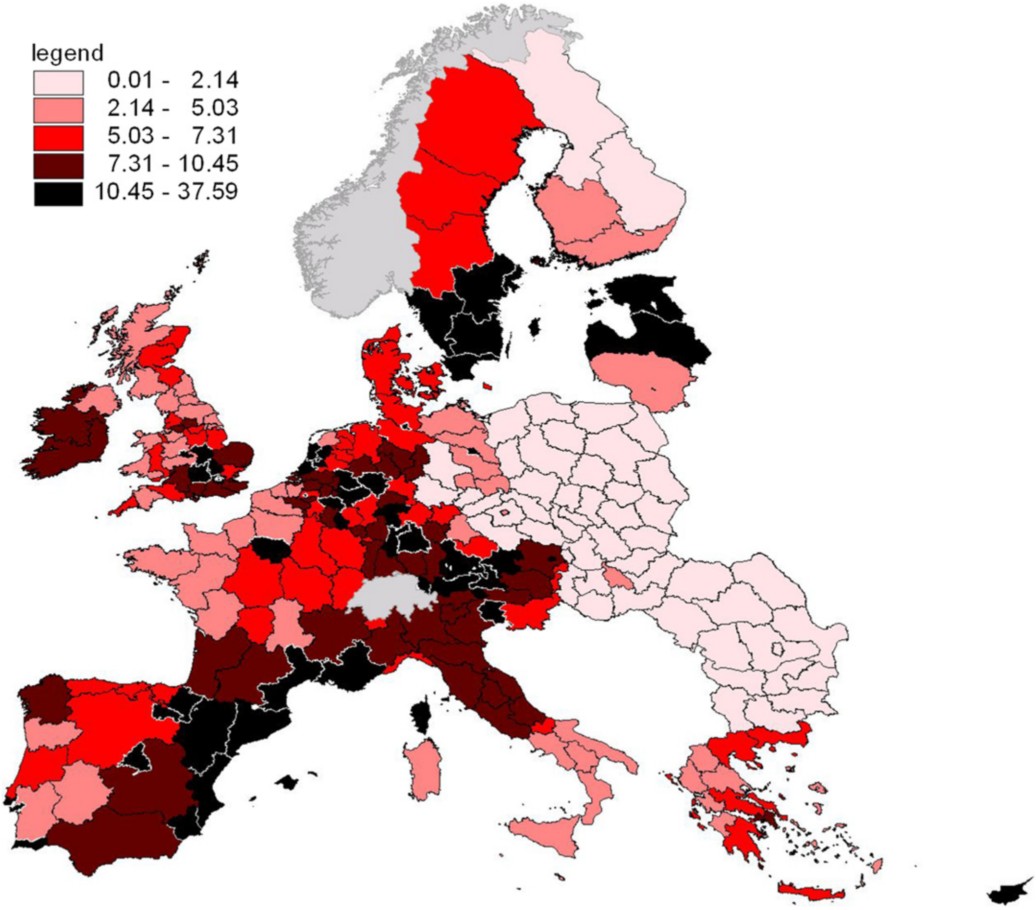

Figure 6. Diversity (percentage of the population born in another country, 2006–7).

economies. In our study, we used two alternative proxies: the settlement structure typology and population density. The first proxy is a more complex indicator of regional hierarchy that distinguishes six types of regions according to two dimensions, density and city size: the less densely populated areas without centers take the value of 1, while the very densely populated regions with large centers, which are the urban areas, take the maximum value of 6. 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 was analyzed by Lorenzen and Andersen (2009) for the case of city regions in northern European countries.

In the econometric analysis, we also controlled for other territorial features by including one dummy variable for the four largest countries in Europe: Germany, France, Great Britain, and Italy. Finally, we controlled for the developmental level of the regional economies by introducing a dummy variable for the "convergence regions," defined as those with a per capita gross domestic product lower than 75 percent of the EU average.

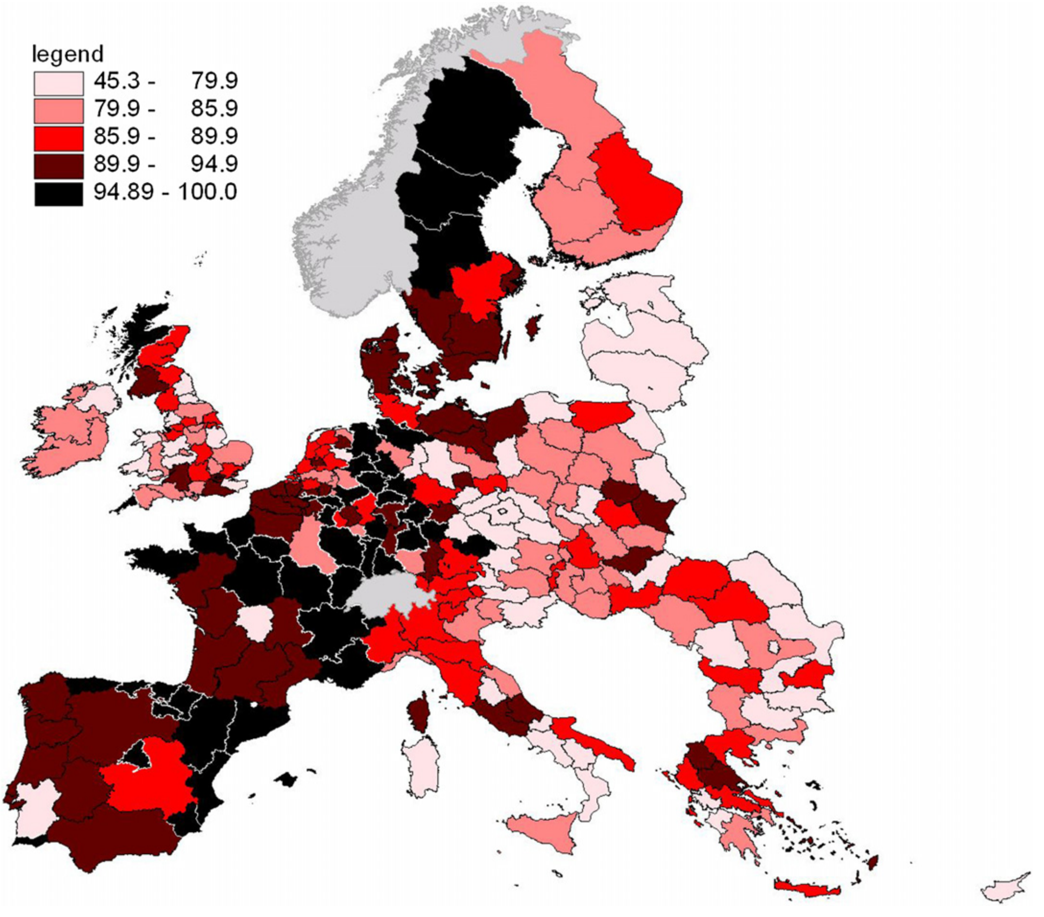

Figure 7. Tolerance (percentage of the population that did not mention "don't like as neighbours: immigrants/foreign workers").

Estimation of Regional TFP

As we mentioned earlier, regional economic performance is represented by TFP, a measure of production efficiency, which allowed us to take into account regional differences in tangible inputs, such as physical capital stock and labor units. For this reason, it is preferred to alternative measures like employment or income growth. We estimated regional TFP by following a quasi-growth accounting approach: rather than impose a priori values for the elasticities of inputs, obtained under the restrictive assumptions of constant returns to scale and perfect competition, we first estimated such elasticities and then used them within a standard growth accounting approach to compute TFP levels.

The regression model we adopted is the log-linearized version of a traditional Cobb-Douglas production function, estimated for the period 1990–2007 for a pooled set of 13 manufacturing and services sectors (agriculture and nonmarket services were excluded) located in each of the 257 European regions:

$$y_{it} = a_i + \alpha\, k_{it} + \beta\, l_{it} + \delta_t + u_{it} \tag{1}$$

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)
Labor units	0.546***
	(0.023)
Time effects	included
R^2	0.785

Note: 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.

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

We estimated the panel model by the Two Stages Least Squares (TSLS) method (the instruments were represented by one-period lagged capital and labor regressors) because of possible endogeneity problems and included time dummy variables (δ_t) to account for macroeconomic shocks, common to all the regions. The productive inputs elasticities (reported in Table 3) were estimated as 0.40 for the capital stock and as 0.55 for the labor units. Since it was not possible to exploit any kind of sectoral breakdown for the explanatory variables included in our empirical models, for consistency, we imposed the elasticities of inputs to be the same across the sectors. However, given the well-documented sectoral heterogeneity (Marrocu et al. 2010), we also considered a regional TFP measure obtained by allowing the coefficients of inputs to vary across sectors. The use of this alternative dependent variable is discussed in greater detail in the robustness analysis presented later.

Turning to our basic measure of TFP, the comparison of the estimated values across the European regions (see Figure 8) not only confirmed the well-known historical divide between the northern and southern regions but also highlighted a striking economic gap between the regions belonging to the EU15 countries and the regions located in the 12 new accession countries. However, in the past decade, eastern European regions have exhibited fast growth, which, at least in the traditional economic sectors, has driven the narrowing of the still-sizable gap.

Model Specification and Estimation Issues

In this section, we present and discuss the econometric analysis we conducted to assess the effects on regional TFP of creativity and high educational levels by considering the concurrent effects of the three categories of human capital we proposed earlier. The empirical model is specified as follows:

$$tfp_i = \alpha + \beta \; human\ capital_i + \gamma \; set\ of\ controls_t + \varepsilon_i \qquad (2)$$

where both the dependent variable and the human capital variable are expressed in per capita terms and are log-transformed. For the basic specification, we controlled for other factors that affect productivity by including the stock of technological capital,

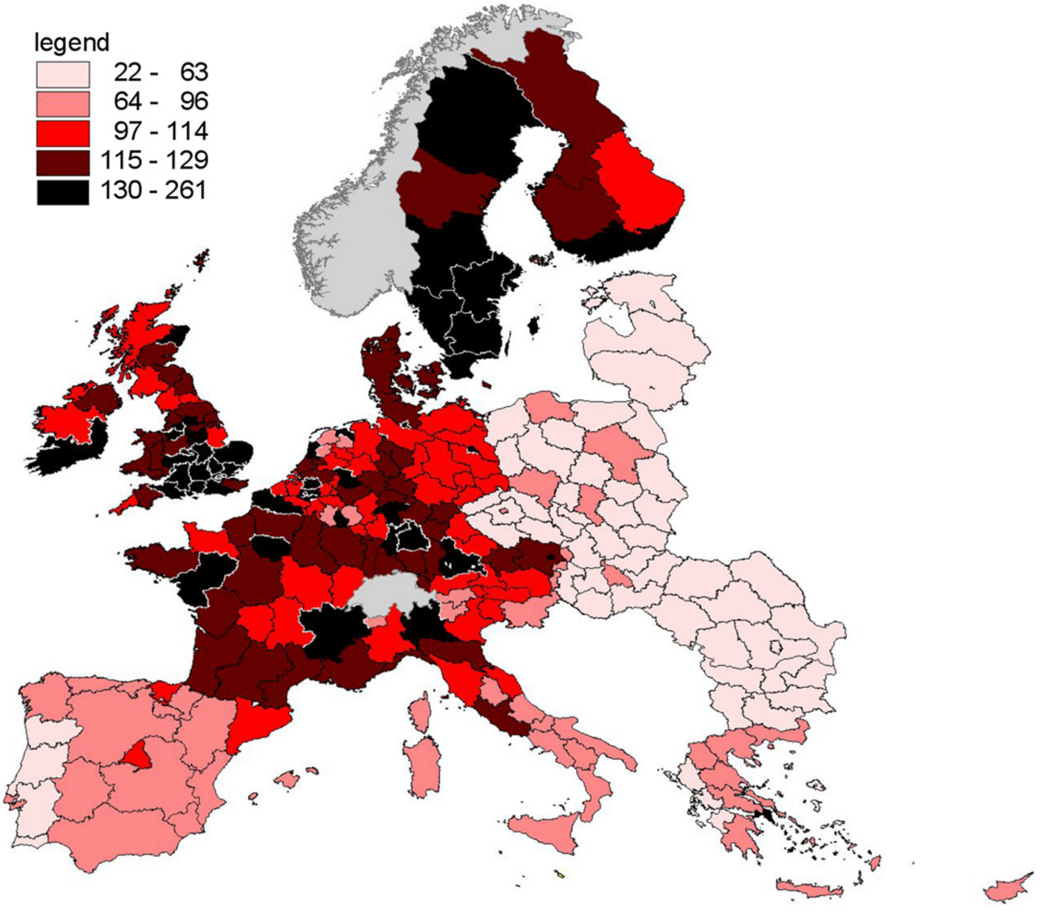

Figure 8. Total factor productivity (index Europe = 100, 2007).

foreign-born people as a percentage of the resident population to proxy the degree of cultural diversity, the manufacturing specialization index, and the settlement structure, which should account for various 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 included a dummy variable for the four largest member countries and a dummy variable for the lagging regions belonging to the EU "convergence objective."

Endogeneity issues may be a potential concern for the estimation of Model (2). However, note that although 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, is doubtful because the link is much more indirect. 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 and the control variables refer to the year 2002.[10] It could be claimed that a 5-year lag is not sufficient to remove

[10] The only exception was the diversity proxy, which is consistently available for all our regions only for the period 2006–7, we elaborate more on this variable when we present the robustness analysis. Moreover, the education and creativity variables were available for all the 257 regions only for 2002, so we could not use previous lags. This lack of data also precluded a panel data analysis.

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)
Noncreative 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)
Manufacturing 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

Note: 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%.

endogeneity if TFP does not exhibit a certain degree of short-term variability. We checked for this possibility 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 out of 257 cases; on the basis of this evidence, we argue that persistence in TFP did not induce any endogeneity problems for our models. For our preferred specification (regression 4 of Table 4) we also conducted a further check by splitting our sample into 2 groups of observations, the top and bottom TFP performing regions, and testing for significant differences in the elasticities of the human capital variables between the two groups. We did not find evidence of any relevant difference, which can be considered an additional indication that there is no positive selection of people with graduate degrees into highly productive regions.[11]

[11] The same kind of results were obtained when we conducted the subsample analysis by dividing the entire sample into the 33 percent–67 percent or 25 percent–75 percent top-bottom performing regions.

Model (2) was initially estimated by ordinary least squares (OLS) and we performed the spatial robust Lagrange multiplier (LM) tests[12] to detect the presence of spatial dependence in the error term or an omitted spatially lagged dependent variable. 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 Kelejian and Prucha (2010), we normalized W by dividing each element by its maximum eigenvalue.[13] The tests provided evidence of spatially correlated residuals,[14] so we respecified Model (2) as a spatial error model with a mean equation as in Equation (2) and a spatial AR model for the error term:

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

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

Assessing the Role of Human Capital

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

Basic Results

To compare our results with the findings of previous studies, we first estimated our models by including one human capital variable at a time; this strategy avoids the multicollinearity problem induced by the high correlation between the two variables (for our sample, the correlation coefficient between the graduates and the creatives is equal to 0.75). We estimated the spatial error model by maximum likelihood (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 explained earlier, 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 substitutes. Therefore, the effects of creatives and graduates should be estimated in the same regression model, otherwise the estimates are biased owing to usual omitted variable problem. We did so in the model reported in column (3), but note that in this case the graduates turned 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 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 may lead to misleading conclusions if measurement issues concerning the disaggregation of human capital are overlooked.

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

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

[14] For the preferred specification (Model 4, Table 4), the robust LM error test was 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 further checks for robustness on the spatial pattern specification are presented in the next section.

Moreover, if human capital indicators are not adequately measured, it is not possible to provide sound policy recommendations based on reliable evidence of the economic role played by creativity and formal education.

In an attempt to reduce measurement problems and thus get more plausible estimated effects the key point is to include regressors that were derived from a more adequate definition of the relevant human capital variables. As we explained earlier and represented in Figure 1, the graduates group was disaggregated into noncreative graduates and creative graduates, with the latter forming the creatives group when considered along with the bohemians.

In the fourth specification reported in Table 4 we included the three nonoverlapping measures of human capital—creative graduates, noncreative graduates, and bohemians—to single out their individual contributions in enhancing regional efficiency. The results indicate that the highly educated creative group is quite relevant in explaining total factor productivity (elasticity estimated in 0.161), followed by the noncreative graduate group (elasticity of 0.043). The bohemian category exhibits a negligible effect,[15] confirming the prominent importance of formal high education in determining economic outcomes in the European regions.

With reference to our preferred specification (Model 4), it is worth stressing that we consider education not 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 since the three human capital subgroups were carefully defined on the basis of the occupational classifications. According to our results, the contribution of the noncreative graduates seems more important for the formation of value added, since they are a relevant component of the labor force. On the other hand, in increasing the level of efficiency, they have an effect evaluated in just one quarter of the effect that is due to creative graduates. This result is not surprising, given that most of the noncreative 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 U.S. metropolitan areas: once the presence of university graduates is properly accounted for, the bohemians are no longer relevant. Similar evidence was found by Nathan (2007) and Nathan and Lee (2011) for U.K. firms and cities.[17]

It is plausible to think that the role played by bohemians is somewhat indirect because their presence may signal—especially to creative graduates—a more open and stimulating working environment. However, they were significantly outperformed in our estimated models by foreign-born people, who are included to approximate the cultural diversity factors. As we stated earlier, we expected this variable to capture the beneficial effects of a more tolerant, inclusive, and open environment that, in turn, would facilitate

[15] Note that the model estimated by OLS returned similar elasticities: 0.17 for creative graduates, 0.05 for noncreative 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 technological capital has a higher VIF value, 4.8, which being less than 6 does not represent an issue); more specifically, for the human capital variables VIF values are 2.2 for creative graduates, 1.4 for noncreative graduates, and 2.1 for bohemians.

[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 lawyers are engaged mostly 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, showed that a significant mismatch is present in the U.K. labor market between those in creative occupations and bohemian graduates, who, despite their often-claimed role in driving economic growth are at a salary disadvantage when compared to nonbohemian graduates. This finding casts further doubts on the economic relevance of the bohemian group.

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, we found a positive significant effect, robust across the alternative specifications we considered, for the technology stock accumulated in the regional economy (0.068); a similar estimate for the technological capital was also reported in Dettori et al. (2011) for the case of the European regions belonging to the EU15 countries plus Switzerland and Norway.

Since the codified knowledge-creation process may depend on the industrial structure, in our models we also included the index of manufacturing specialization; this index turned out to be negatively associated with the TFP levels, signaling that a regional industrial structure that specializes in manufacturing sectors does not seem to favor efficiency enhancements. This finding may be due to the fact that the innovative drive of such production has been accomplished, especially in the most advanced western economies, as we noted earlier. Another possible explanation for this result is that differences in the agglomeration economies that are due to the production structure are more adequately captured by the settlement structure. This variable is positively and significantly correlated with TFP, signaling that more urban and densely 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 controlled for other specific local characteristics by including two dummy variables for the convergence regions and for the four largest countries, which exhibited the expected negative and positive sign, respectively. This finding provides further evidence that when the intangible efficiency determinants are held constant, TFP is, on average, lower in the converging regions (see also Figure 8), while being a region of the four largest countries counterbalances the previous effect for the poorer regions and increases the productivity for the richer ones.

Robustness Analysis on Human Capital Classifications

In this section, we discuss the empirical analysis we conducted 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 the most relevant distinguishing feature to be talent, rather than formal education. If there is a measurement problem because some bohemians are also graduates, it should yield even more unfavorable evidence. As we emphasized earlier, we did not have additional information to check for this aspect in our data, so we conducted a simple robustness exercise by assuming that such a measurement error could be equal, on average, to 20 percent of the people in the bohemian group being misclassified; since these people are actually graduate workers, they should be included in the creative graduate group.[18] We, therefore, redisaggregate 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]

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[18] For Italy, using the microdata from the labor force survey, we calculated that the share of graduates in some occupations included in the bohemians group is 18 percent.

[19] We also experimented with different proportions of misclassification error (in the range 10 percent–30 percent), and the results for Model (4) were extremely robust.

Table 5

Robustness Analysis of the Human Capital Variables

Dependent variable: total factor productivity, 2007				
Spatial error models				
	1	2	3	4
Checking for the misclassification of	Bohemians[a]	Archivists and Librarians[b]	Directors and Managers[c]	
Human capital				
Creative graduates	0.167***	0.146***	0.140***	0.199***
	(0.052)	(0.052)	*(0.053)*	*(0.072)*
Noncreative 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*Technological 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)*
Manufacturing 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 correlation, actual and fitted values	0.814	0.817	0.815	0.818

[a] The creative graduates variable increased by an amount equal to 20 percent of the bohemians variable, the latter decreased accordingly; see the text for details.
[b] Archivists, librarians, and related information professionals (ISCO 88 code 243) were dropped from the creative graduates group and included in the noncreative graduates one.
[c] Directors and chief excutives (ISCO 88 code 121) and general managers (ISCO 88 code 131) were dropped from the noncreative graduates group and included in the creative gradutes one.
Note: Estimation method: ML. Observations: 257 regions. All regressions include a constant term. Human capital variables, diversity, and technological capital were 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%.

In the second regression, we assessed whether the creative graduates coefficient may 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. Therefore, we dropped them from the creative graduates group and included them in the noncreative graduates group.

We addressed the opposite misclassification problem in the third regression, where we checked whether the same coefficient could be biased because we excluded from the group of creative graduates the subgroups of directors and general managers (ISCO 88 codes 121 and 131), who could be expected to perform creative tasks in managing firms or in proposing innovative organizational solutions. Therefore, we moved them from the noncreative to the creative graduates group.

The estimated coefficient for the creative graduates is robust; it decreased slightly to a point estimate of 0.14 and remained highly significant in both regressions 2 and 3 of Table 5. In contrast, the coefficient for the noncreative graduates group was drastically reduced to an estimate of 0.008 when directors and general managers were no longer included. This result was clearly driven by the fact that they accounted for, on average, about 4.5 percent of the noncreative graduate population. Moreover, it highlights how low is the contribution to productivity enhancement of the remaining occupations (just 2.7 percent of the initial noncreative graduates group), represented mainly by legislators, senior governmental officials, legal professionals, and business professionals.

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

The empirical results of both the basic model and the alternative specifications, which allowed us to control for potential errors in the identification of the three nonoverlapping categories of human capital, provided robust evidence of 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 entire EU, it appears that both Glaeser's (2005) claim on education and Florida's (2002) intuition on creativity are consistent. Indeed the effects of creativity can unfold only when high levels of formal education are present, while the economic relevance of creativity per se seems scarce.

Robustness Analysis on Model Specification and Control Variables

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

Alternative Model Specifications

In the first two columns of Table 6, we present alternative ways to deal with the spatial dependence present in the data with respect to the basic model (regression 4 of 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. Because of the presence of spatial spillovers,[20] the estimates of the coefficients cannot be compared with the ones reported in Tables 4 and 5, but the estimated total effects (0.17 for creative graduates, 0.05

[20] In the case of the lag model, the interpretation of the estimated coefficients as partial derivates with respect to a specific regressor no longer holds because of the presence of the spatially lagged dependent variable, which induces feedback loops (a given region is the neighbor of its neighbors, so that affecting them receive in turn feedback effects) and spillovers 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, generated by the change in a certain region's own regressor, and the indirect effect due to spillovers (Le Sage and Pace 2009).

Table 6

Robustness Analysis of the Spatial Specification and 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)*
Noncreative 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)*
Manufacturing 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 correlations, actual and fitted values		0.848	0.828	0.876

Note: when not otherwise indicated, the model specification is the spatial error one; the dependent variable is the 2007 TFP variable, calculated by applying common sectoral input elasticity; 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 were log transformed and are 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 on request.

for noncreative graduates, and a non significant –0.03 for bohemians) are 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 model in capturing geographic dependence across regions.

As a further check, we re-estimated the basic model by adopting an alternative spatial weight matrix, the contiguity one. The results are qualitatively similar to those of the basic model, both for the human capital indicators and for the control variables. It is worth noting that the creative graduate elasticity decreases to 0.11 and that of noncreative graduates decreases to 0.03, while the bohemians keep exhibiting a nonsignificant effect; the estimated spatial error correlation coefficient (0.66) points out a weaker 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 than is the inverse distance one.

The last two regressions enabled us to assess the robustness of human capital effects when we considered a different way of computing the dependent variable. In the first case (Model 3), to smooth away undue business cycle effects, rather than use the 2007 TFP level, we calculated the 5-year average over the period 2003–7.

In the second case, to account for the high sectoral heterogeneity that characterizes the elasticities of inputs, we computed the 2007 TFP level for each region as the weighted average of 13 sectoral TFP levels obtained using the elasticity of inputs estimated without imposing homogeneity restrictions across sectors.

According to the results of specifications 3 and 4 of Table 7, the evidence provided by our basic model is robust, with the creative graduates outperforming the noncreative ones, and the bohemians still having no predictive power. Therefore, we can confidently rule out that the diversified effects of the human capital indicators previously discussed could be driven by the specific way in which we computed our preferred regional measure of economic performance or by the way we accounted for spatial dependence.

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 we selected. Overall, the impacts of the human capital variables are robust across the five different models we considered and in line with those provided for the basic model, even if there is some evidence of slight variability.

Since, as we mentioned earlier, no data were available on foreign-born people in 2002 for all the new accession countries regions, we were forced to use 2006–7 data[21] to estimate the models reported in Table 4. However this, again, could raise some endogeneity concerns because of reverse causality, since foreign-born people may be attracted by high-performing regions. To check for this possibility, we re-estimated our preferred basic specification by using census data on foreign population for 2001, which, regrettably, were available for NUTS2 regions only for a reduced subsample (193 regions out of the 257).[22] 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 results for the human capital variables are robust, exhibiting only slightly reduced elasticities with respect to the preferred specification. Thus, using the most recent data on residents born in another country did not seem to alter the estimates for the whole sample in a remarkable way.[23] We also control for cultural diversity factors by considering a direct measure of tolerance, given by the percentage of the resident population that did not dislike having foreign people as neighbors. This new control was included in regression 2 of Table 7; although it shows a positive coefficient estimate, it was not significant at conventional levels and remained so even when we considered an alternative specification (not reported) where it replaced the share of the foreign-born population. This result may be due to the fact that the data available for a direct proxy of tolerance are not informative

[21] See footnote 10.

[22] No data on the foreign-born population are available for Malta, for the Belgian, German, and Greek regions.

[23] 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, since it requires data from a far distant previous period disaggregated by immigrants' countries of origin, which are not available for all the regions included in our sample.

Table 7

Robustness Analysis of the 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)*
Noncreative 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)			
Manufacturing 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 correlations, actual and fitted values	0.826	0.814	0.805	0.811	0.826
Observation	193[a]	257	257	257	257

Note: Estimation method: ML for spatial error models. All regressions include a constant term. Human capital variables, diversity, and technological capital were log transformed and are 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 and the Belgian, German, and Greek regions are not available.

enough to capture such a complex phenomenon; a deeper investigation of the "tolerance" aspects of the local economic environment is left for future research.

Considering the other regional controls, we tested whether the specialization pattern is better represented by the specialization index for knowledge-intensive sectors rather than the one for manufacturing, which had an adverse effect on productivity according to the results of the basic model. Because efficiency gains may be expected for economies specialized in the most innovative sectors, in the third model of Table 7 we tested this conjecture by including the corresponding specialization index. Although the coefficient sign is now positive, it is significant only at the 17 percent level. As we mentioned earlier, industry specialization indexes are outperformed by the settlement structure indicator, which, accounting for both population density and the presence of large centers, is superior also with respect to the simple population density variable (Model 4).

Finally, we tested 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 temperatures were less productive. The creative graduate and noncreative graduate variables remained positive and significant with slightly lower elasticities, 0.12 and 0.03, respectively, when compared to those of the basic model.

In sum, we think that the analysis presented in this article 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 same people within a productive environment. At the same time, our results show that once we adequately controlled for educational attainment, we found no direct economic role for the bohemians component across all the different estimated specifications.

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 is not disputed. In recent years, the focus has been actually shifted to investigating its specific characteristics and components even further to attain a better understanding of the interactions among human capital, geographic features, and firms' localization strategies.

After the success of Florida's (2002) book, which suggested 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 policy perspective, emphasizing 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 those in the sciences, engineering, education, culture, the arts, and entertainment. However, the lack of a clear definition of what creativity actually entails and the extent to which it differs from traditional measures of human capital has led to a wide array of particular classifications, crucially dependent on the aim of the specific empirical analysis they were included in. The problem of the relevant overlapping of the concepts of education and creativity noted by Glaeser (2005), although often acknowledged, has not been consistently addressed in empirical analyses, 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 article we aimed to contribute to the "Florida versus Glaeser" debate by proposing a disaggregation of human capital into three nonoverlapping categories to overcome the measurement problem of the creativity and educational components of human capital. We identified three categories—creative graduates, bohemians, and noncreative graduates—by combining the information on educational attainments with the data on actual occupations in an attempt to account for the concurrent effects of both potential and actual on-the-job skills.

Since the three groups do not overlap and are supposed to capture different characteristics of the human capital phenomenon, they were all included in our empirical models, allowing us to provide reliable and sound evidence on their impacts on regional productivity. This was an issue in previous empirical analyses because to avoid multicollinearity, induced by the overlapping of graduates and creative class variables, the latter (or even subgroups of them) were included one at a time, thus resulting in biased estimates if education and creativity are expected to be complementary, rather than substitute, determinants of economic outcomes.

Once the three human capital categories were identified, we evaluated their effect on TFP, the most comprehensive efficiency indicator of economic performance, for 257 regions belonging to EU27. It is important to remark that this was the first time that this analysis was conducted for such a large sample of regions covering the entire European Union, thus providing more general and robust empirical results than would a single-country study. We estimated the effects of human capital from spatial error models that controlled for regional geographic features and for characteristics of the local environment, such as cultural diversity, technological capital, industrial structure, and an 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 noncreative graduates group, whose effect appears to be approximately a quarter of the impact of the first group. Arguably, the role played by noncreative graduates is confined mostly to the formation of value added. This result was driven mainly by the fact that most of the noncreative graduates are employed in occupations that are related to civil service, business, and legal jobs. The bohemians turned out to be not significant once we accounted for the presence of the creative graduates group.

The evidence provided on the diversified effects of the human capital categories is robust to an extensive set of robustness checks, including possible misclassification issues in our grouping approach. The results also confirm the relevant influence exerted by technological capital, cultural diversity, industrial structure, and settlement pattern, thus providing further empirical support for the claim that an innovative, open, inclusive, and culturally mixed environment is becoming more and more vital for enhancing productivity.

We think that the analysis presented here 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 basis for reconciling the up-to-now opposite views of Florida's supporters, on one side, and Glaeser's followers on the other. Florida was correct because our analysis confirmed that talent matters: university graduates who work in noncreative professions tend to be less productive than do those who use their talents on actual jobs. At the same time, our findings confirmed Glaeser's hypothesis that education is a crucial determinant of economic performance because the talent of graduates has a greater impact than does the talent of bohemians.

In conclusion, our key result is that although higher education remains one of the most relevant factors in driving economic outcomes, it is important to acknowledge that its effectiveness varies according to the creativity content of the graduates' actual occupations. The most effective role is played by graduates who are employed in occupations that are characterized 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 who work in other occupations. In this picture, there is no room left for an independent direct effect on productivity exerted by the bohemian group. Creativeness per se does not seem to influence regional economic performance, although it may contribute to a stimulating and enjoyable environment, thus acting as a signal of a favorable working location, especially for creative graduates.

From a policy-making perspective, these results call for more effective national and regional policies that aim to increase access to higher education and to support university degrees that are linked to the more creative fields of the sciences, engineering, and education; at the local level, urban planning should aim to ensure that the European regions become more attractive to skilled people, not just to 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 were not considered.

Appendix 2. Data Sources and Definition

Variable	Label	Description	Primary Source
Value added	Y	Millions of euro, prices 2000, 1990–2007	Cambridge Econometrics
Capital stock	K	Millions of euro, prices 2000, 1990–2007	Own calculation
Units of labor	L	Unity of labor, 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 the ISCO classification), 2002	Labour Force Survey
Bohemians	B	Creative bohemians employment, thousands (see Table 1 for the 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
Noncreative graduates	NCG	Differences between graduates and creative graduates employment, thousands, 2002	Own calculation
Technological capital	TK	Patents stock, years 2000–4	CRENoS on EPO
Diversity	DIV	Population born in another country, thousands, 2006–7 (alternative proxy: foreign population over resident population, Census 2001)	Eurostat
Manufacturing specialization	MAN	Specialization index of manufacturing employment, 2002	Eurostat
Knowledge specialization	KIS	Specialization index of knowledge-intensive service employment, 2002	Eurostat
Settlement structure typology	SST	1 = less densely populated without centers, 2 = less densely populated with centers, 3 = densely populated without large centers, 4 = less densely populated with large centers, 5 = densely populated with large centers, 6 = very densely populated with large centers, 1999	ESPON project 3.1 BBR
Population density	DEN	Population per km2, thousands, 2002	Eurostat
Tolerance	TOL	Population that did not mention “don’t like as neighbours: immigrants/foreign workers”, %	EVS
Climate	TEMP	Annual average temperature	ESPON 2013 program
Dummy convergence regions	DCONV	Dummy variable for the “convergence regions” (< 75 percent of the EU GDP average)	Eurostat
Dummy large countries	D4	Dummy variable for the 4 largest EU countries (Germany, France, the United Kingdom, and Italy)	Own calculation