From creativity to innovativeness: Micro evidence from Italy

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Abstract

In this paper I assess the existence, and the magnitude, of knowledge externalities in the form of creativity spillovers that affect firm innovative performance. Relying on a large sample of Italian manufacturing firms, I estimate a knowledge production function and I regress the residuals, namely 'innovativeness', on a set of creativity indicators, while controlling for endogeneity and nonlinearity. My estimates show that there is a positive effect of creativity on innovativeness, whereas the effect on actual innovative sales is weak. In particular, I find that such a positive effect is higher when referring to less qualified creative workers rather than to highly qualified ones. Moreover, I find that the relationship between firm innovativeness and the regional density of creative workforce is endogenous and U-shaped, so that creativity spillovers materialize only in creativity denser urban contexts.

Keywords: creativity; innovativeness; knowledge production function; nonlinearity

JEL: L60; O31; R10

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1. Introduction

Does the local availability of creative workers increase firms' innovative performance? The answer to this question has received little attention in the quantitative economic geography literature. In particular, the recent debate has been focused to estimating the effects of creativity on regional development variables like population or employment growth (Marlet and van Woerkens, 2007; McGranahan and Wojan, 2007; Boschma and Fritsch, 2009; Andersen et al., 2011), entrepreneurship (Lee et al., 2004; Wojan and McGranahan, 2007; Boschma and Fritsch, 2009), regional wages (Florida et al., 2008; Mellander and Florida, 2011), and TFP (Marrocu and Paci, 2011). Instead, less attention has been devoted to innovation variables, which can be used for explaining the productivity effects of creativity, especially after the diffusion of microeconometric studies on the role of innovation output as a main determinant of the heterogeneity in the levels of productivity among firms (Crépon et al., 1998; Lööf and Heshmati, 2002; OECD, 2008). Given such a strong correlation between innovation output and productivity, if also a strong correlation between creativity and innovation output is found, then a link between creativity and productivity can be traced.

With this idea in mind, I improve the current debate on the economic effects of creativity in two ways. First of all, I focus on a direct measure of innovation output, rather than on measures of innovation input, like R&D, or measures of invention, like patents. In this way, I provide an innovation-based explanation for better understanding the mechanism through which creativity impacts regional development. To the extent that firm productivity is affected by innovation output, rather than by innovation input, then it becomes crucial to understand if the local availability of creative workers does have an effect on the capability of firms to generate innovations and to successfully sell them into the market. In so doing, I also provide some explanation on how creativity and firm innovation performance relate to each other: according to my estimates, local creativity spillovers do not affect much the actual, observed, innovation performance of firms – which is explained more by the in-house availability of R&D labour and capital - but, rather, it relates to 'what is left behind' by the standard linear model of R&D and innovation, as estimated through the knowledge production function (KPF hereafter). Thus, creativity can be thought as a tool for developing and commercializing new products in alternative to R&D and the other formal inputs of the innovation process.

Secondly, in the same vein of Moretti (2004a), I provide a more direct approach to the assessment of human capital externalities, which is based on the estimation of firm-level KPF rather than focusing on a city region level of analysis.

The paper is organized as follows. In Section 2, I briefly sketch the motivation and the conceptual background of the paper. In Section 3, I first describe the data and the measures of creativity employed (3.1); then, I describe the dependent variables of innovation and the econometric specifications adopted for estimating the KPF (3.2). In Section 4, I present the empirical results on the actual innovation output (4.1) and innovativeness (4.2) respectively, and I dwell upon endogeneity and non-linearity issues (4.3). Finally, Section 5 concludes.

2. Conceptual framework: how does creativity foster regional development?

According to the literature, creativity is considered as a form of human capital, which fosters local economic growth through three main mechanisms (Black and Lynch, 1996; Glaeser, 1999; Moretti, 2004a, b; Florida, 2002a; Marlet and van Woerkens, 2007). First, the local concentration of human capital contributes to knowledge accumulation and sharing, making all the people operating in the same area more productive, particularly in high-tech industries. Second, higher concentration of human capital increases the local rate of entrepreneurship by favouring the birth, and development, of new firms. Third, human capital may act through consumption and spending activities, under the assumption that high-skilled people earn higher wages than less skilled ones.

In this work I focus on the first mechanism. In particular, I propose an explanation for the link between regional growth and the local concentration of creative workforce based on firm innovation activity. Since "creativity involves thinking that aims at producing ideas or products that are relatively novel and that are, in some respect, compelling" (Sternberg 2006, p. 2) and "it is a matter of sifting through data, perceptions and materials to come up with combinations that are new and useful" (Florida 2002a, p. 35), the most direct way through which creativity may affect local competitiveness is through the development of new ideas, i.e. through innovation.

One way by which this occurs is, for instance, through design. On this purpose, Hollanders and van Cruysen (2009, p. 5) provide cross-country evidence about the interplay between creativity, i.e. the generation of new ideas, design, i.e. the shaping of new ideas into new products, and innovation, i.e. the exploitation of ideas through the successful marketing of new products. At the European level, Ciriaci (2011) also finds that design has a strong positive impact on firms' innovative performance, regardless of the size of the firm. Concerning Italy, Bertacchini and Borrione (2012) show that design industries are highly relevant sectors in the creative economy, especially in non-urbanized areas.

Another way is simply through social connections, i.e. weak ties that develop in social networks that are rooted in particular places where culture is produced and consumed. Such a mechanism is well described as follows: "[p]eople talked. They compared notes. They changed

jobs. And when one engineer or designer meets with another to talk about how a new computer's design will fit with the hardware inside, or whether a particular fabric will work with a designer spring collection, chances are they exchange a lot of ideas […] The exchange of knowledge ended up translating into new ideas and product innovations" (Currid, 2007, p. 71). Moreover, "[…] firms have to know where to find the skills they need, and the potential employees have to make themselves known. Social networks are simply the best and most efficient way to do this" (Currid, 2007, p. 84).

With this framework in mind, I do expect that firms located in places with a high concentration of creative workers show a higher innovative performance than firms located elsewhere. In addition, as typical in spatial agglomeration studies, I do also expect that such a relationship can be non linear. This nonlinearity can emerge because of the presence of congestion costs or because of the need for regions to reach a critical mass of creative capital before making knowledge to diffuse and spill over.

3. Data and methodology

3.1. Data and creativity variables

Data come from the 10th Survey on manufacturing firms administered by Unicredit bank group (formerly Mediocredito Centrale and Capitalia). This survey gathers information on a representative sample of 5137 Italian manufacturing firms over the period 2004-2006. Firms with more than 500 employees are fully represented while firms employing more than 11 and less than 500 employees are selected on the basis of the region of location, the employment size and the sector of economic activity. This survey provides useful information on firm innovative activities, including R&D and the share of innovative sales, as well as other information concerning the labour force composition, the internationalization activities, and the market relationships between the firm and its banks, customers and competitors.

Data have been cleaned from non manufacturing firms, inconsistencies and missing observations in the variables of interest, namely innovative sales and total turnover, so to reach a final sample of 3197 firms. Table 1 shows its distribution by employment size, macro-area (NUTS1) of firm location and industry (according to Pavitt taxonomy).

Data on creativity, instead, come from the Census of Population and Housing carried out by the Italian Statistical Office (ISTAT) in 2001. Following Florida (2002), I rely on four employment-based measures of creativity, each one measured at the level of NUTS3 regions, which in Italy

correspond to the 103 Adminisrative Provinces[1]. The first, and also the broader in scope, is the numer of "workers developing a technical, administrative, organizational, intellectual, scientific, sporting or artistic activity for whch it is required a medium or a high level of specialization". This is the Creative Class varable (CC), which includes many types of knowledge-based occupations, irrespective of the level of education or qualification. In order to disentangle the role of education, in the spirit of Glaeser (2005), I split this variable in two main elements: qualified crative workers (QC) and non qualified creative workers (NQC). The former includes "technical, scientific, organizational, intellectual, sporting and artistic occupations with a high level of qualification or specialization", i.e. for which, typically, a tertiary level of education is required. The latter, instead, includes "technical, administrative, sporting and artistic occupations with a medium qualification", i.e. typically for which a secondary school diploma is required. With some cautions, I consider the former as a measure of the so called *creative core*, and the latter as a rough measure of the stock of *bohemians*. Finally, I also consider the number of employees with a tertiary education degree, irrespective of their occupation (EDU). This variable allows me to include a standard measure of human capital in the estimates, and to compare it with the previously described creativity-based measures of human capital.

Relying on these variables, I then consider two types of indicators for the estimates. The first is a location quotient of creativity, as given by the share of creative workers in the NUTS3 region with respect to the same share in the NUTS2 region (i.e. the 20 Administrative Regions in Italy). In so doing, I consider four location quotients, one for each type of creative class considered: LQ(CC), LQ(QC), LQ(NQC), LQ(EDU). The second is a density measure of crativity, given by the number of creative workers per squared kilometer of NUTS3 land area. As before, I generate four density variables, which I put in logarithmic form: Ln(DenCC), Ln(DenQC), Ln(DenNQC) and Ln(DenEDU). In order to capture potential nonlinear effects, I also include in the estimates the squared terms of these variables. The logic, now, is to capture the effect of spatial proximity on innovation: as density increases, so it makes the probability for firms to match creative workers. Therefeore, I do expect that the innovation performance of firms increases as they locate in creativity-denser areas.

[1] According to Boschma and Fritsch (2009), this spatial level is particularly relevant for analysing the relationship between the creative class and regional economic development as the place of residence and the place of work usually coincide within the same region. Bertacchini and Borrione (2012) argue that NUTS3 regions are a good balance between descriptive accuracy and statistical noise regarding the specialization of provinces in creativity.

Figures 1 and 2 show the distribution of creativity acrosws Italian NUTS3 regions in 2001: in particular, Figure 1 maps the regions that are specialized in creative occupations (i.e. with a value of LQ(CC) bigger than one) while Figure 2 maps the quartile distribution of the density measures of creativity.

3.2. Innovation variables and KPF estimates

The KPF is a relationship linking innovation inputs to measures of innovation output (Griliches, 1979). For instance, if I is the share of innovative sales for firm i and L_R, K_R and K_{ICT} are the variables, respectively, of R&D labour, R&D capital and ICT capital, we can write the following standard Cobb-Douglas version of the KPF:

(1) $I_i = A_i L_{iR}^{\alpha} K_{iR}^{\beta} K_{iICT}^{\gamma}$.

Creative capital (K_C) located in region p can enter the KPF in two ways. It can be considered as a direct input, thus acting as a multiplicative term in equation 1 (and as an additive term once we express it in natural logarithms). Alternatively, it can contribute explaining the term A, as follows (and once transformed in natural logarithms):

(2) $\ln A_i = \delta K_{C\,p} + u_i$.

Following the accounting framework developed by Mairesse and Mohnen (2001, 2002), I identify two indicators of innovation output. The first is the expected share of innovative sales in total turnover, namely the percentage of innovative sales that can be expected for a firm when controlling for a number of explanatory variables that affect innovation activity. This variable can be conceived as a sales weighted measure of the number of innovations, and is explained by an explicit econometric model or accounting framework. Table 2 shows its sample distribution by firm size, area of localization and sector of activity.

The second variable represents the “extent of innovative ability or capacity” of a firm (Mairesse and Mohnen, 2002, p. 226), namely its innovativeness. While innovative sales can be considered like the expected output of innovation activity, as explained by the underlying innovation model adopted, innovativeness can be taken as the unexplained, or unexpected, part of the actual observed share of innovative sales, which remains unaccounted for by the model as it stands. According to Mairesse and Mohnen (2001, 2002), innovativeness is to innovation what TFP

is to output: both account for omitted factors of performance like technological, organizational, cultural, environmental, or social factors which are not captured by the innovation and the production function respectively. In their words: "both also correspond to other sources of misspecification and errors in the underlying model of the innovation or production function, and could be rightly viewed as measures of our ignorance" (Mairesse and Mohnen 2001, p. 8).

Therefore, firm innovativeness is computed as the residual from a model which explains innovation performance as function of a series of variables of firm size, sectoral specialization, organizational structure and innovation input, as provided by a well established microeconometric literature on the determinants of innovation.

As previously mentioned, the variable measuring the actual observed innovation output is the share of total sales coming from new products[2]. This variable has two features which make standard OLS estimates unreliable: first, it is a proportion bounded between 0 and 1; second, it has a left-skewed distribution. In order to tackle these issues, I estimate the KPF following the standard microeconometric literature on innovation (Crépon et al, 1998; Mairesse and Mohnen, 2001, 2002) and applying a logit transformation to the share of innovative sales. The logit share of innovative sales (y) is, thus, defined as $\ln[y/(1-y)]$; in this case, all the zero values are excluded from the computation, so that the number of observations reduces to 1397. Since not all firms are innovative, and a potential selection bias may arise, I specify the KPF in terms of a generalized Tobit model (Heckit henceforth) with two equations: the first accounts for the propensity to innovate, as measured by a dummy variable which takes the value of 1 for firms recording a positive share of innovative sales, while the second accounts for the intensity of innovation, as measured by the logit share of innovative sales.

As regressors in the selection equation, which models the firm propensity to innovate, I take the following variables: firm size (Size), as given by the log of average 2004-2006 turnover[3]; group membership (Group), as given by a dummy equal to 1 for firms belonging to a business group; consortium membership (Consortium), as given by a dummy equal to 1 for firms belonging to a credit, export, R&D or to another type of consortium; a dummy for firms engaged in exporting activities (Export); a dummy equal to 1 if the firm benefited from tax reliefs in 2004-2006 (Tax reliefs); three variables of cooperation activities, as given, respectively, by the share of financial contribution to extra-mural R&D expenditures coming from universities and research centres (Coop

[2] Differently from the CIS, the Unicredit survey does not specify if the product is new to the firm or to the market.

[3] Due to the presence of many missing values, I decide not to include the traditional variable of log employment. However, the correlation between the two variables is around .5, and significant at 1% level.

Univ/Res), other firms (Coop firm), and other organizations (Coop other), like trade fairs, associations, conferences, showrooms and so on[4]. Finally, I also include 22 two-digit industry-specific dummies in order to control for technological conditions and sector-specific effects.

For what concerns the outcome equation, I exclude the tax reliefs dummy and I extend the set of regressors to the following variables: R&D labour, namely the average share of R&D workers in 2004-2006; a dummy for process innovation (Process innovation); the log value of average innovation input expenditures, including R&D, design, training, and expenditures in machinery and equipment (Ln Input); the log value of average expenditures in information and communication technologies (Ln ICT).

Table A1 in the Appendix shows the results of the Heckit estimate for this basic specification. The residuals of the outcome equation are then extracted and used for computing firm innovativeness. Table 3 shows its sample distribution according to firm size, NUTS1 area of firm location and industry. Interestingly, innovativeness is higher, on average, for small sized firms, located in the North East and South of Italy and for firms belonging to the scale intensive and supplier dominated sectors, this latter including most of the Made in Italy industries.

4. Estimation results

4.1. The impact of creativity on actual innovation intensity

The first exercise consists in estimating the effect of the local availability of creative workers on the observed innovative performance of firms, as measured by the actual (logit) share of innovative sales. On this purpose, I estimate two sets of models, as given in Table 4. In the first (columns 1 to 4), next to the other variables of firm size, group, consortium, export, cooperation, R&D and ICT capital, I include the various LQ indicators of creativity, i.e. LQ(CC), LQ(QC), LQ(NQC) and LQ(EDU). Due to their high mutual correlation (around 0.8 on average), I include them separately in the estimates. In the second (columns 5 to 12), I separately include the density measure of creativity and their squared terms.

From Table 4 we observe that only the local availability of bohemians (NQC) seems to affect actual innovation intensity, even if the effect is rather weak (marginal effect 0.04 and significant at 10%). The estimated coefficients of LQ(QC) and LQ(EDU), although positive, are not statistically different from zero. Moreover, when including the squared terms of each LQ, the estimated coefficients (not reported here) are never statistically different from zero.

[4] Differently from the CIS, I do not have here information on factors hampering innovation activities.

When we look at the density measures, I first find that, when excluding the squared terms, the estimated coefficients are never statistically different from zero (columns 5, 7, 9 and 11). When I include the squared term (columns 6, 8, 10 and 12), the coefficients of creativity become statistically significant, and follows a U-shaped relationship with innovative sales. In particular, I find that, in order for a positive relationship to emerge, Italian provinces should reach a minimum threshold of 47 CC per squared km, which becomes 16 for QC, 29 for NQC, and 23 for EDU. All these values are largely above the median level of regional creativity density[5], but, due to the generally little size of Italian cities, they concern a bulk of eleven provinces only, namely Genoa, Milan, Naples, Rome, Prato, Rimini, Trieste, Varese, Lecco, Como and Padua, eight of them located in the North.

Interestingly, the threshold level for tertiary educated is higher than the one for graduated creative people: I interpret this as a sign of a potential additive effect of creativity to education in creating knowledge spillovers.

4.2. The impact of creativity on firm innovativeness

Tables 5 shows the estimation results for the impact of creativity on firm innovativeness, computed as the residual from the estimate of the Heckit model of the KPF, as specified in Table A1 in the Appendix.

In order to avoid collinearity with the control variables included in the KPF, and looking at the heterogeneous distribution of innovativeness as shown in Table 3, in estimating equation 3 I include the following controls: four NUTS1 area dummies (North West, North East Centre and South), three size dummies, one for small firms (11-49 employees), one for medium firms (50-249) and one for large firms (more than 250 employees); two sectoral dummies for firms operating in medium-high and high-tech industries versus medium-low and low-tech ones (as defined by EUROSTAT); one dummy for firms located in NUTS3 regions hosting one of the 32 larger urban zones (LUZ), defined by EUROSTAT as enlarged areas including the city and its surroundings. For reasons of space, Table 5 reports only the estimated coefficients of creativity variables.

Looking at the location quotients, I now register a positive and significant (at 5%) effect of creativity on innovativeness. In particular, a unit increase of regional specialization in creative jobs increases the unexpected innovation intensity of firms by 1.08 percentage points. Interestingly, I also find that the impact of NQC (+1.45) is more than double than the one of QC (+0.62) and for EDU (+0.61).

[5] These median values amount, respectively, to 27 workers per km^2 for CC, 9 for QC, 19 for NQC and 12 for EDU.

With respect to density measures, I still observe that, when the squared terms are excluded, the estimated coefficients are never statistically different from zero. When I include them I find a strong nonlinear effect: in particular, now NUTS3 regions should reach a minimum threshold of 38 CC per squared km, 13 QC, 26 NCQ, and 18 EDU in order to make manufacturing firms to increase their innovativeness. As before, only firms located in a small number of regions can benefit from creativity spillovers.

Summing up, positive knowledge externalities in the form of creativity spillovers affecting firm innovativeness seem to emerge only in creativity denser regional contexts and are like to be higher for bohemians than for specialized creative, as well as for highly educated, workers. This evidence can find different explanations. The first is that creative people have not necessarily to be highly educated for generating and spreading new ideas (Florida, 2002a, Marlet and van Woerkens, 2007, Andersson, 2011). In other words "[i]t's not so much how much education they had […] as much as it was about what people did with their human capital and how they used their creativity and ideas. […] For example, an artist, writer or musician may not have a bachelor degree, but the jobs themselves require constant innovation. Superstar innovators like Bill Gates are college dropouts, yet masterminds in technological advances for society" (Currid, 2007, pp. 69-70).

The second reason relies on the characteristics of the Italian economy, as primarily driven by high-quality craft-based productions located in small municipalities (Micelli, 2011; Bertacchini and Borrione, 2012). In this case, I can expect a higher benefit to come from the local interaction with medium, or even low, qualified creative workers, rather than from tertiary educated creative people.

Third, the effect of QC can be partly included in the estimated coefficient of R&D labour in the KPF. If creative people with a university degree are reasonably engaged in formal intra- and extra-mural R&D activities, then there can be a potential double-counting effect on this variable[6] which lowers its coefficient.

Finally, another plausible explanation is that the local availability of QC does affect more the inventive activity of firms (i.e. trough patenting), rather than their innovation output. This idea is in line with Florida's (2002) and UNCTAD (2010) distinction among three types of creativity, i.e. technological (more related to invention), economic (more linked to entrepreneurship) and artistic/cultural creativity, and is confirmed, for instance, by Carlino et al. (2007) for the US and by Boschma and Fritsch (2009) for seven European countries, excluding Italy.

[6] Unfortunately I cannot control for this issue, since I do not know the number of creative workers employed in each firm.

I then try to test for this hypothesis by looking at the relationship between creativity and the number of per-capita inventions submitted to the European Patent Office by firms located within Italian provinces. Since I do not have firm-level information on patents, I rely on NUTS3 level data on inventions and trademarks provided by the Italian Ministry of Economic Development on European Patent Office data, for the period 2004-2006. Therefore, as dependent variable, I consider the number of inventions (patents, trademarks and models) per million of inhabitants (in natural log). As regressors, in addition to my creativity measures, I consider also the log of per-capita value added (lnVA) and the log of population density in year 2001 (lnPOP), in order to control for income and urbanization effects. Results from standard OLS estimates are presented in Table 7[7]. As expected, I find that the rate of invention is affected only by the relative share – as well as by the density - of QC, whereas no effect is registered for NQC[8].

Hence, this result is in line with the idea that the most educated creative workers are 'repository' of technological creativity, whereas less qualified ones are more related to the concept of economic creativity and to the development of business-related activities (UNCTAD, 2008)[9]. In addition, this result reminds the concept of informal communities as a key intermediary between individuals and firms in developing new ideas. According to Cohendet et al. (2010, p. 94), "if skilled individuals are very active in the beginning of the creative process, communities are essential in the elaboration of a common grammar on which creative ideas are developed. As new expressions are progressively reinforced, firms and other formal institutions replace the two preceding entities and therefore become essential in bringing the new ideas to the market".

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[7] I also control for potential endogeneity bias by estimating the regional patent equation with a GMM-IV approach. In all cases, the endogeneity test does not reject the null hypothesis of exogeneity (see Section 4.3 for details). In addition, these results may be potentially biased by spatial autocorrelation: however, it is not the purpose here to estimate the precise impact of creativity on the rate of invention, but, rather, to focus on its sign and statistical significance.

[8] These results are also confirmed when I take, as dependent variable, the number of patents, trademarks and models separately. Results are available on request.

[9] An indirect proof of this idea is also given by the level of education of entrepreneurs in Italy: according to ISTAT (2006, p. 11), the major part of Italian entrepreneurs hold, in 2005, a secondary school degree (46%), then a primary school degree (32%) and, finally, a tertiary school degree (22%).

4.3. Endogeneity and nonlinearity

As typical in agglomeration studies, the relationship between the outcome variable (here innovation output) and its explanatory variable (here creativity) can be endogenous. Such endogeneity can basically arise because of: (i) simultaneity between the dependent variable and the covariates; (ii) unobserved heterogeneity due to the existence of unobservable factors which affect innovation output and are not related to creativity.

In absence of panel data, I try to overcome the first problem by relying on a five years time lag between innovation output and creativity measures, the former being measured in 2006 and the latter in 2001. With respect to the second issue, I first saturate the estimates with controls on size, industry and other firm-level activities. Second, I re-estimate the two models with a GMM instrumental variable (GMM-IV) procedure, in which, as instrument, I use a cultural capital index for each NUTS3 region, given by the number of art galleries, museums, public libraries and tourists per inhabitant in year 2001, as provided by Unioncamere (2004). In so doing, following the literature (Florida 2002a; Marlet and van Woerkens 2007; Wojan and McGranahan 2007; Florida et al. 2008; Mellander and Florida 2011), I assume that the creative class is attracted not only, or not much, by high-income cities, but also by ‘culturally attractive’ cities, with a high degree of openness, diversity and tolerance[10] (UNCTAD, 2010; Simonton, 2011).

For each GMM estimate, I then compute the corresponding endogeneity test, which, in the case of a cluster-robust estimates, is given by the Wooldridge (1995) robust score test. Results of these tests are reported in the last row of Tables 4 and 5[11]. When looking at LQ measures of creativity (Table 4), the null hypothesis of exogeneity can never be rejected, so that these variables should be taken as exogenous and OLS estimates as consistent. However, when looking at the density measures, the null hypothesis of exogeneity is rejected at 10% level, so that these second set of variables should be treated as endogenous, although this endogeneity is rather weak.

[10] As a robustness check, as instrument in the GMM-IV estimates I use the Tolerance index developed by Florida and Tinagli (2005). Since the correlation with the amenity index is high (almost 0.6), results are pretty much the same.

[11] For what concerns the KPF estimates, in testing the endogeneity of creativity in the Heckit model I run an OLS estimate on the restricted sample of innovative firms only, and I include the inverse of the Mills ratio (computed from a first-stage Probit estimate on the propensity to be innovative) in order to control for potential selection bias.

On this purpose, I re-estimate equation 2 by GMM-IV, using the previously described cultural capital index as instrument (Table 6)[12]. Interestingly, I register a positive and significant effect of the density of creative workers on firm innovativeness. However, such an effect is 'filtered' by the availability of local cultural capital. This means that, on the one hand, culturally open and dynamic regions are able to attract a higher mass of creative workers; on the other, once localized in these regions, these creative workers – bohemians in particular – use the locally available cultural capital for creating and diffusing knowledge on the territory. In other words, creativity and cultural capital are two inputs in the innovativeness function.

As explained in Section 2, in addition to endogeneity, a second issue that typically characterizes the studies on agglomeration concerns the presence of nonlinearities. On the one hand, congestion effects may give rise to a hump-shaped relationship between innovative output and creativity. On the other, creativity spillovers may realize only after a density threshold is reached: in this case, the relationship between creativity and innovation would become U-shaped.

In order to test for the presence of nonlinear effects, I first introduce in the estimates the squared terms of the density variables[13], as reported in Tables 4 and 5. Then, I also test for the strength of these nonlinearities by separately estimating a set of generalised additive models (GAM) of innovation output (both actual and residual) on the density of creative workers and by minimizing a penalized log likelihood function. The smoothness of the resulting estimated function is given by the specified 'equivalent degrees of freedom', in this case two (Hastie and Tibshivani, 1990). The presence of a curvilinear effect of second order is given by the magnitude, and statistical significance, of the so called 'gain' statistics, which corresponds to the difference in normalized deviance between the GAM and a model with linear term for creative workers density: the larger the gain, and the higher its significance, the higher is the non-linearity.

Results from the test are shown in Table 8. Looking at the magnitude of the gain statistic and to its level of significance, it is clear that a true nonlinearity emerges only with respect to innovativeness, whereas the level of significance in the case of the actual innovative sales is always above 5%. This means that the non linear effects found in Table 4 are weak, as confirmed in Figure 3 column a by the width of the 5% confidence intervals area. Figure 3 column b, instead, shows the

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[12] To give an idea of the goodness of the amenity index as an instrument for the density of creative workers, I regress each of the four density measures of creativity on NUTS1 area, size, industry, LUZ dummy and the amenity index, obtaining a value of R^2 equal, on average, to 0.54, with the coefficient of the amenity index significant at 1% level. Dropping amenities as an explanatory variable, the value of R^2 lowers to 0.35 an average.

[13] In unreported estimates, I also introduce the cubic terms, but they are never statistically significant.

U-shaped relationship between innovativeness and the log density of creativity: in line with Table 7, now the thinness of the 5% confidence interval area signals that positive knowledge spillovers from proximity to creative workers truly emerge only when regions reach a minimum density threshold.

These results can have a twofold theoretical interpretation. On the one hand, it can be that only after a certain density of creative capital, firms and creative workers are able to minimize their mutual search and job matching costs. On the other, following Jacobs (1969), it can be that a critical mass of creativity is crucial for making cultural producers to meet each other and sustain themselves through social ties: "the concentration of creativity leads to greater chances of more creativity happening", so that "[t]he greater number of creative people lends itself to great possibilities for new innovations, artistic collaborations, and possibilities of discovery of new types of music, fashion, and art" (Currid, 2007, p. 91).

5. Conclusions and policy implications

In this paper I estimate the magnitude of knowledge externalities in the form of creativity spillovers which affect the innovation performance of firms. By exploiting a rich dataset on Italian manufacturing firms, I find that, in general, the higher the local availability of creative workers, the higher the innovation capability of firms. This effect is particularly true when we look at the unexplained part of the innovation output, namely innovativeness, rather than at the observed share of innovative sales. This latter is explained more by standard variables of size, industry specialization, export, and innovation input like R&D.

Interestingly, when I control for the level of qualification of creative workers, I find that innovativeness is more affected by the local availability of the low-qualified ones, whereas highly qualified creative workers seem to contribute more to the regional invention rate. In addition, when I measure creativity through a standard education-based indicator, estimated coefficients are always slightly lower than the occupation-based ones. Therefore, traditional measures tend to underestimate the impact of human capital on firm innovative performance.

The existence of knowledge spillovers is also confirmed when I measure creativity in terms of density. However, such a relationship is endogenous and seems to emerge only when I instrument for the local availability of cultural capital. Therefore, creative workers and cultural capital are two factors that concur to explain firm innovativeness.

Finally, creativity and innovativeness are linked by a U-shaped relationship, so that positive knowledge externalities arise only after a certain critical mass of creative workers is reached.

From the policy point of view, I argue that increasing the availability of creative jobs and people can foster firms' capability to generate, and exploit, new ideas, especially in the absence of

large R&D departments and formal agreements with external partners. In this respect, my results are in line with the literature on *innovative milieux*, where social learning phenomena, rather than formal R&D activities, help explaining the processes of knowledge creation and diffusion within and between firms, clusters and territories. Moreover, this evidence is also in line with Glaeser (1999), who argues that workers learn quickly if they are located within large urban contexts. Therefore, in order for proximity-based knowledge externalities to emerge in the process of exploration and exploitation of new ideas, cities or regions have to be 'large' enough: in this sense, a potential selection effect on larger, and more urbanized, areas may emerge (Andersen et al. 2011). In other words, only large city-regions can provide the chances, and the institutions, for making creative workers to meet, exchange ideas, and find jobs and salaries.

However, once such a positive effect of creativity is triggered, then a potential impact on firm productivity may also occur. To the extent that productivity is primarily affected by innovation output (Crépon et al., 1998), then, in the absence of congestion costs, a virtuous circle from creativity to firm productivity can also emerge, in the spirit of the endogenous growth theory (Lucas, 1988).

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Table 1. Sample distribution by size, area and industry (Pavitt classification)

Size	**Clean**	**Original**
11-20	32.22	33.50
21-50	30.50	30.66
51-250	29.87	27.66
251-500	4.00	4.57
> 500	3.41	3.60
Area		
North West	41.26	42.88
North East	29.97	29.04
Centre	16.86	16.24
South	11.92	11.84
Pavitt		
Supplier dominated	49.36	49.74
Scale intensive	18.89	18.96
Specialized suppliers	27.49	26.75
Science based	4.25	4.56
N. obs.	**3197**	**5137**

Table 2. Average innovative sales by size, area and industry

Size	**Full sample**	**Innovative sales >0**
11-20	9.61	27.66
21-50	10.30	24.68
51-250	13.36	26.05
251-500	11.68	23.36
> 500	17.84	24.94
Small	9.95	26.07
Medium	13.36	26.05
Large	14.51	24.23
Area		
North West	10.89	26.11
North East	11.52	24.92
Centre	14.10	29.36
South	8.26	21.70
Pavitt		
Suppl. Dominated	11.05	26.70
Scale intensive	9.02	25.24
Special. Suppliers	12.30	24.47
Science based	17.98	28.43
Average %	11.31	25.88
Num. obs.	**3197**	**1397**

Table 3. Average innovativeness by size, area and industry

Size	**Innovativeness**
11-20	2.058
21-50	1.813
51-250	1.595
251-500	1.315
> 500	1.169
Area	
North West	1.761
North East	1.653
Centre	1.878
South	1.685
Pavitt	
Suppl. Dominated	1.830
Scale intensive	2.086
Special. Suppliers	1.491
Science based	1.477
Average	1.741
Num. obs.	**1397**

Table 4. Knowledge production function estimates: impact of creativity measures on the logit share of innovative sales

Heckit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LQ(CC)	0.341											
	(0.320)											
LQ(QC)		0.202										
		(0.202)										
LQ(NQC)			0.736**									
			(0.337)									
LQ(EDU)				0.147								
				(0.164)								
Ln(DenCC)					0.037	-0.406**						
					(0.035)	(0.162)						
Ln(DenCC^2)						0.058***						
						(0.020)						
Ln(DenQC)							0.035	-0.280**				
							(0.034)	(0.109)				
Ln(DenQC^2)								0.056***				
								(0.018)				
Ln(DenNQC)									0.038	-0.356**		
									(0.035)	(0.150)		
Ln(DenNQC^2)										0.058***		
										(0.020)		
Ln(DenEDU)											0.036	-0.298**
											(0.033)	(0.121)
Ln(DenEDU^2)												0.053***
												(0.018)
Num. obs.	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197
Uncensored	1397	1397	1397	1397	1397	1397	1397	1397	1397	1397	1397	1397
Endogeneity test	0.025	0.091	0.005	0.221	0.247		0.269		0.237		0.244	
(p-value)	(0.874)	(0.764)	(0.942)	(0.640)	(0.621)		(0.605)		(0.628)		(0.623)	

Notes: NUTS3 region-level clustered-robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All the estimates also include the explanatory variables included in the ‘Outcome’ column of Table A1 in the Appendix.

Table 5. The impact of creativity on innovativeness: OLS estimates

Heckit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LQ(CC)	1.075**							
	(0.441)							
LQ(QC)		0.621**						
		(0.301)						
LQ(NQC)			1.446***					
			(0.495)					
LQ(EDU)				0.613***				
				(0.229)				
Ln(DenCC)					-0.912***			
					(0.315)			
Ln(DenCC^2)					0.125***			
					(0.040)			
Ln(DenQC)						-0.573***		
						(0.197)		
Ln(DenQC^2)						0.112***		
						(0.036)		
Ln(DenNQC)							-0.850***	
							(0.241)	
Ln(DenNQC^2)							0.131***	
							(0.035)	
Ln(DenEDU)								-0.638**
								(0.249)
Ln(DenEDU^2)								0.110***
								(0.042)
Num. obs.	1397	1397	1397	1397	1397	1397	1397	1397
R^2	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Endogeneity test	0.576	0.751	0.492	0.438	3.055	2.931	3.127	2.791
(p-value)	(0.450)	(0.388)	(0.485)	(0.510)	(0.084)	(0.090)	(0.080)	(0.098)

Notes: bootstrapped (50 reps.) standard errors are reported in brackets. Estimates also include four area dummies (NUTS1), three size dummies (small, medium , large), two industry dummies (high-tech Vs low-tech) and one metropolitan city dummy. * significant at 10%; ** significant at 5%; *** significant at 1%. All the estimates also include the explanatory variables included in the 'Outcome' column of Table A1 in the Appendix. Endogeneity test for columns 5 to 8 refer to the model without squared terms.

Table 6. The impact of creativity on innovativeness: GMM-IV estimates

	OLS				GMM-IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(DenCC)	0.037				0.189**			
	(0.044)				(0.094)			
Ln(DenQC)		0.040				0.176**		
		(0.046)				(0.087)		
Ln(DenNQC)			0.035				0.197**	
			(0.059)				(0.098)	
Ln(DenEDU)				0.043				0.173**
				(0.046)				(0.085)
Num. obs.	1397	1397	1397	1397	1397	1397	1397	1397
1st stage R^2					0.53	0.54	0.53	0.55
2nd stage R^2	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03

Notes: cluster-robust standard errors are reported in brackets. Estimates also include four area dummies (NUTS1), three size dummies (small, medium , large), two industry dummies (high-tech Vs low-tech) and one metropolitan city dummy. * significant at 10%; ** significant at 5%; *** significant at 1%. All the estimates also include the explanatory variables included in the 'Outcome' column of Table A1 in the Appendix. Instrument: amenity-based index including the number of art galleries, museums, public libraries and tourists per thousand inhabitants in year 2001.

Table 7. The impact of creativity on the regional invention rate

Variables	(1)	(2)	(3)	(4)	(5)	(6)
LnVA	2.297***					
	(0.397)					
LnPOP	0.789***					
	(0.150)					
LQ(CC)	2.905**					
	(1.150)					
LQ(QC)		2.406***				
		(0.831)				
LQ(NQC)			0.857			
			(1.690)			
Ln(DenCC)				2.773**		
				(1.110)		
Ln(DenQC)					2.761***	
					(0.608)	
Ln(DenNQC)						0.723
						(1.527)
Num. obs.	103	103	103	103	103	103
R^2	0.502	0.525	0.471	0.485	0.538	0.452

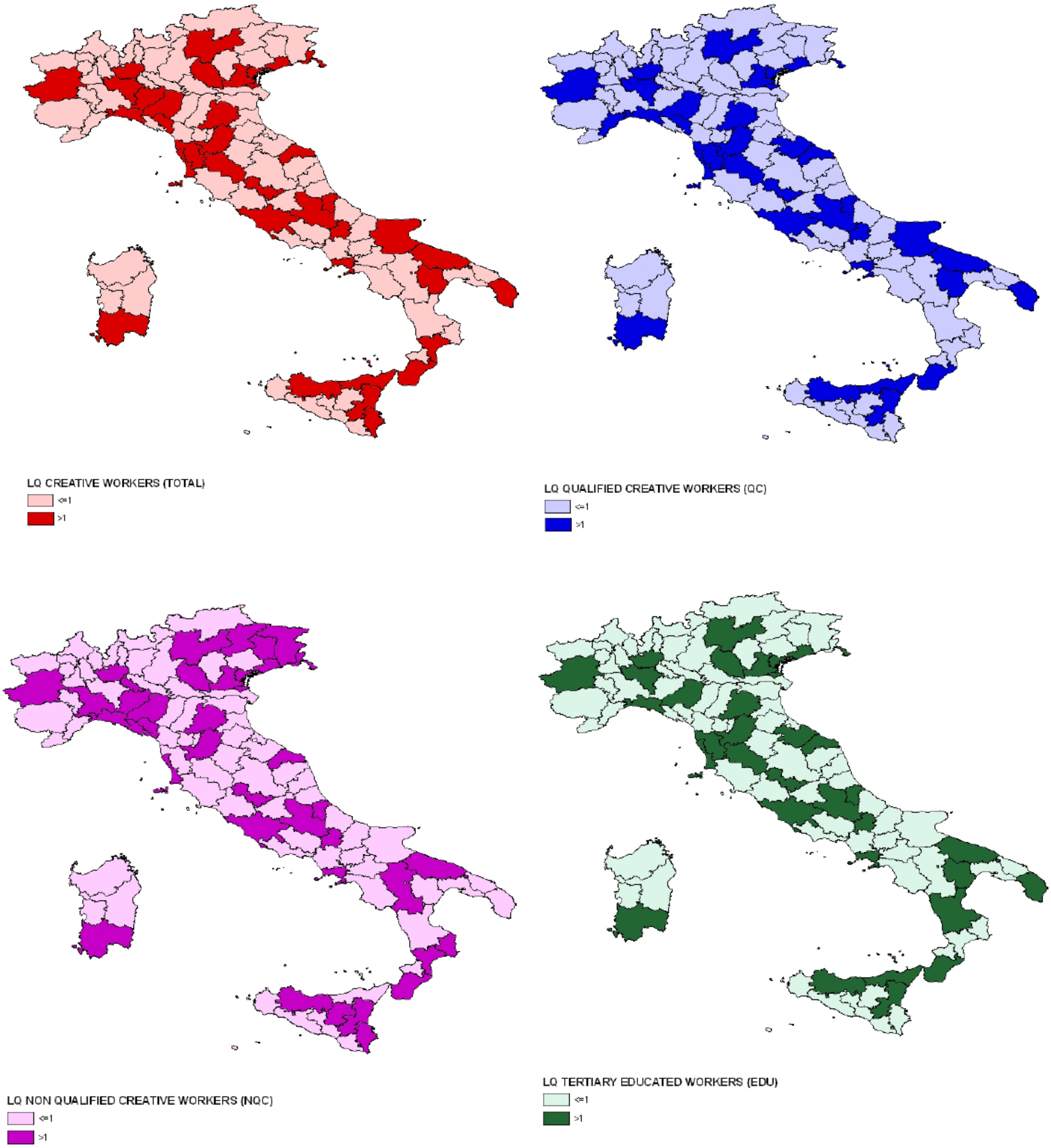
Notes: heteroskedasticity-robust standard errors in brackets. All the estimates also include a constant term. Dependent variable is the 2004-2006 average number of inventions (patents, trademarks, prototypes) per 1000 inhabitants registered at the European Patent Office (natural log).

Table 8. Generalized additive model estimates on creativity density

Density variables	**Innovative sales**
Ln(DenCC)	3.417 (0.065)
Ln(DenQC)	3.589 (0.059)
Ln(DenNQC)	3.229 (0.072)
Ln(DenEDU)	3.162 (0.076)
	Innovativeness
Ln(DenCC)	9.783 (0.002)
Ln(DenQC)	8.836 (0.003)
Ln(DenNQC)	10.227 (0.001)
Ln(DenEDU)	8.714 (0.003)

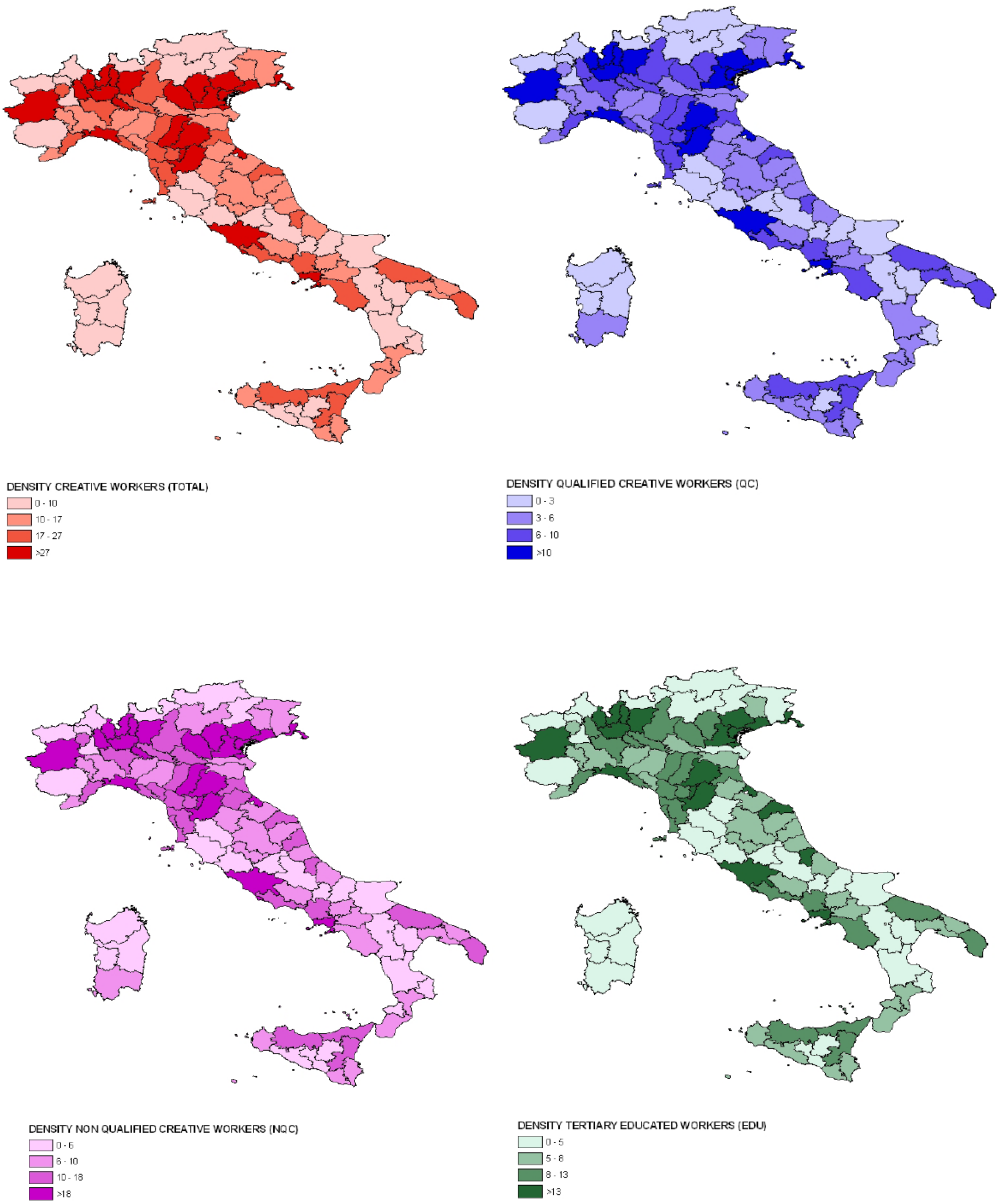
Notes: p-values in brackets.

Figure 1. The geographic distribution of creative workforce in Italy (2001)



Source: Census of Population and Hiusing (ISTAT, 2001).

Figure 2. The density of creative workforce in Italy (2001)

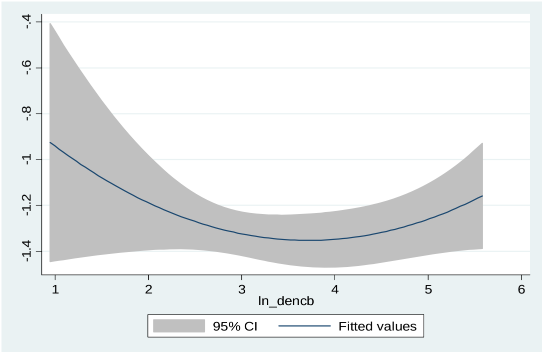


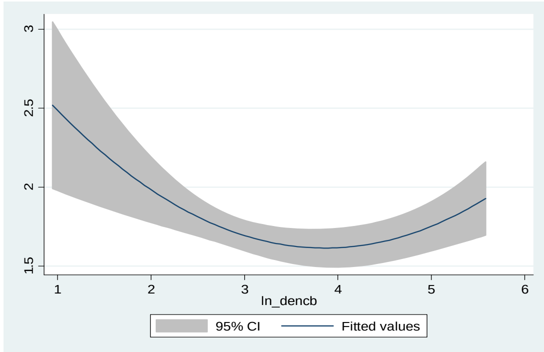
Source: Census of Population and Housing (ISTAT, 2001).

Figure 3. The relationship between the log density of creative workers and innovation output

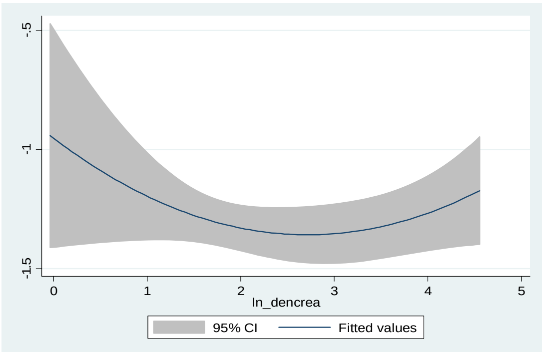
(a) Innovative sales **(b) Innovativeness**

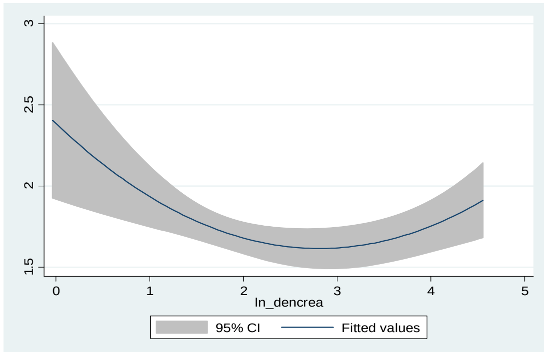
Ln(DenCC)



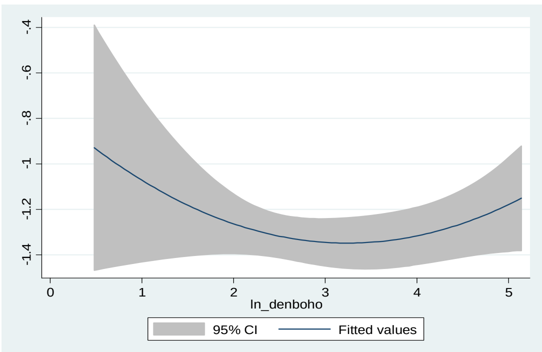


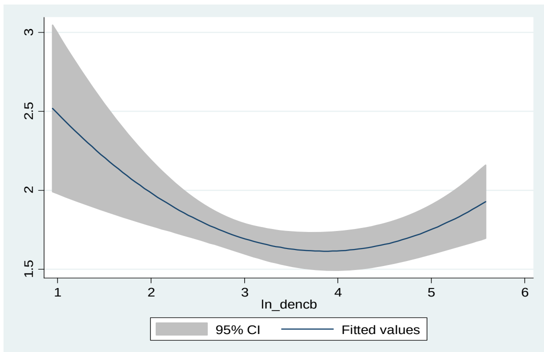
Ln(DenQC)



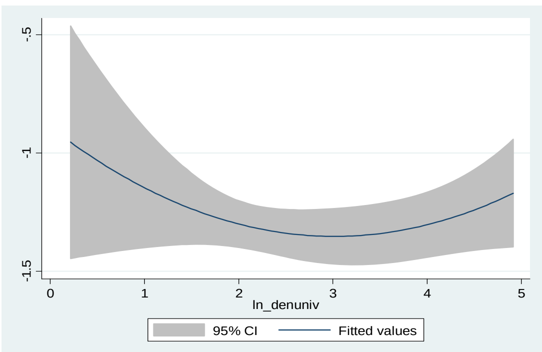


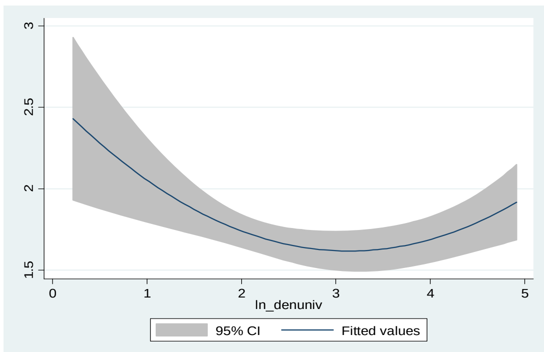
Ln(DenNQC)





Ln(DenEDU)





Appendix

Table A1. Knowledge production function estimates: basic specification

	Heckit	
	Selection	**Outcome**
Group	-0.016	-0.087
	(0.048)	(0.119)
Consortium	0.304***	0.691***
	(0.104)	(0.233)
Size	0.133***	0.145***
	(0.017)	(0.046)
Export	0.237***	0.303***
	(0.055)	(0.115)
Tax Reliefs	0.087**	
	(0.044)	
Coop Univ/Res	0.221*	-0.088
	(0.124)	(0.221)
Coop Firm	0.050	0.118
	(0.190)	(0.442)
Coop Other	0.534***	0.711***
	(0.082)	(0.167)
R&D labour		0.876***
		(0.233)
Process innovation		0.221***
		(0.065)
Ln Input		0.394*
		(0.227)
Ln ICT		1.181
		(1.003)
Industry dummies	Yes	Yes
Num. obs.	3197	1397
Log pseudo LL	-4466.43	
Lambda	2.118***	

Notes: NUTS3 region-level clustered-robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.