Antonietti, Roberto

Conference Paper

From creativity to innovativeness: micro evidence from Italy

52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia

Provided in Cooperation with:
European Regional Science Association (ERSA)

Suggested Citation: Antonietti, Roberto (2012) : From creativity to innovativeness: micro evidence from Italy, 52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:
https://hdl.handle.net/10419/120581

From creativity to innovativeness: micro evidence from Italy

Roberto Antonietti

Department of Economics and Management "Marco Fanno"
University of Padova
Via del Santo 33
35123 Padova (Italy)
E-mail: roberto.antonietti@unipd.it

Abstract

In this paper I assess the existence, and the magnitude, of technological externalities in the form of creativity spillovers that affect individual firms' innovative intensity. Relying on a large sample of Italian manufacturing firms, I first estimate a knowledge production function through a zero-inflated beta regression model and a generalized Tobit model. From these, I extract the residuals, which represent the unexplained part of the actual observed share of innovative sales, namely innovativeness. Then, I regress such a measure of firm innovativeness on a set of occupation-based, as well as density-based, indicators of creativity at the NUTS3 level, while controlling for firm localization, size and industry. I also control for endogeneity and non-linearity by estimating a two-stage least squares model and a generalized additive model respectively. My estimates show that: (i) there is a positive and highly statistically significant effect of creativity on innovativeness; (ii) the effect of creativity on actual innovative sales is weak, while I find a stronger effect played by the availability of R&D labour within the firm; (iii) occupation-based measures of creativity outperform education-based measures of human capital; (iv) when controlling for the education content of jobs, firms' innovativeness is affected more by the local availability of non-graduated creative workers than of graduated ones; (v) rather, relying on NUTS3 regional data, I find that a higher local availability of graduated creative workers affects the invention intensity of a city; (vi) the relationship between firm innovativeness and the local density of creative people is U-shaped, so that proximity-based knowledge externalities emerge only after a certain density threshold is reached, this occurring typically in larger urban areas, typically hosting design and service-based creative industries. From the policy point of view, increasing the availability of creative jobs and people can help regions and cities to be more innovative, 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.

Keywords: creativity; innovativeness; innovative sales; knowledge production function; proportions

JEL: L60; O31; R10

"[*U*]*ntil very recently it was rare to find innovation research applied to creative industries. We suspect this is due to two factors: first, that they were generally seen as 'frivolous' […]; second, because much novelty is seen to involve aesthetic issues, fashion trends, and the sorts of content discussed at length by media and cultural studies. Determining what is original in aesthetics and content is a minefield which innovation researchers are understandably wary of*" (Miles and Green, 2010, p. 185)

1. Introduction

Does the local availability of creative workers help firms increase their innovative intensity? The answer to this question, although intuitive, has received little attention in the quantitative economic geography literature. In particular, the recent debate has been oriented to estimating the effects of creative capital on variables of regional development 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 Total Factor Productivity (Marrocu and Paci,. 2011).

Less attention, instead, has been devoted to the link between creative capital and innovation activity, especially after the diffusion of firm-level studies linking innovation output to productivity (Crepon et al., 1998; Lööf and Heshmati, 2002; OECD, 2008). In this respect, the key hypothesis of this paper is that, given the existence of a strong correlation between innovation output and productivity, if a strong correlation between creativity and innovation output is also found, then a link between creativity and productivity can be produced.

With respect to the previous literature, I improve the debate in two ways. First of all, my focus is on a direct measure of innovation output, rather than being on a measure of innovation input (like R&D) or on a measure of invention (like patents), or even on macroeconomic variables of economic growth. In this way, I provide an innovation-based explanation for better understanding the mechanism through which creativity impacts on regional development. To the extent that firm efficiency and productivity are affected by innovation output, rather than by innovation inputs (Crepon et al., 1998; OECD, 2008), then it becomes crucial understanding 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 intensity relate to each other: according to my estimates, local creativity does not affect much the actual, observed, innovation performance of firms – which is explained more by the availability of R&D resources within the firm - but, rather, it helps explaining (in part) '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 line with Moretti (2004a), I provide a more direct approach to the assessment of human capital externalities, which is based on the estimation of plant-level knowledge production functions 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 result for 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 economic growth?

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

In this work I particularly focus on the first mechanism. In particular, I propose a complementary explanation of the link between regional growth and the local concentration of creative people 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, that is 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, as the generation of new ideas, design, as the shaping of new ideas into new products, and innovation as the exploitation of ideas, i.e. the successful marketing of these 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 need freelancers and contract workers as well as a permanent creative labor force, while creative people need employment, both temporary and long term. […] Regardless, 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 firm located in places with a higher density of creative workers – or a higher specialization in creative jobs - show a higher innovative performance than firms located elsewhere. In addition, I also do expect that a non-linear relationship may characterize such a relationship. This nonlinearity emerges because of the presence of congestion costs, or, on the contrary, because of the need for cities to reach a critical mass of creativity before making knowledge to diffuse and spill over (Jacobs, 1969; Currid, 2007).

3. Data and methodology

3.1. Data and creativity variables

Data come from the X Survey on manufacturing firms administered by Unicredit bank group (formerly Mediocredito Centrale and Capitalia). The Survey gathers information on a representative sample of 5137 Italian manufacturing firms for 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 in which they are located, the employment size and the sector of economic activity. This Survey contains several useful information on firm innovative activities, like R&D, investments in new equipment, ICT, product and process innovation 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, 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 Pavitt industry. As can be seen, firms distribution in the cleaned sample is almost the same as in the original one, thus leaving its representativeness unaltered.

Data on creativity, instead, come from the Census of Population 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 corresponds 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 qualification". This is my Creative Class varable (CC), which includes many types of knowledge-based occupations, irrespective of the level of education or qualification acquired. In order to disentangle the role of education, in the spirit of Marrocu and Paci (2011), I split this variable in two main categories: *qualified cratives* (GCR) and non qualified creatives. The former category 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

[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. Also, Bertacchini and Borrione (2012) argue that NUTS 3 regions are a good balance between descriptive accuracy and statistical noise regarding the specialization of provinces in creativity.

as a measure of the so called *creative core*, and the latter as a rough measure of the share of *Bohemians*, or, in Cohendet et al. (2010) words, a measure of the *underground groups*[2].

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 so to compute the contribution of education to creativity spillovers and to compare it with the creativity-based measures of human capital (Glaeser, 2005; Marrocu and Paci, 2011).

Relying on these variables, I define two types of indicators to be included in the estimates. The first is a location quotient (LQ) of creativity, as given by the share of creative workers in the NUTS3 region with respect to the same share at the NUTS2 region (i.e. at the level of the 20 Administrative Regions in Italy). In so doing, I consider four location quotients, one for each category of creative class considered (LQCC, LQGCR, LQBohemians). The second is a density measure of crativity, computed as the number of creative workers per squared kilometer of NUTS3 land area. As before, I generate four density variables, which I put in logarithmis form: Log(DenCC), Log(DenGCR), Log(DenBohemians) and Log(DenEDU). In order to capture possible threshold or congestion efefcts, I also include in the estimates the squared terms of these variables.

Figures 1 and 2 show the quartile distribution of creativity over Italian NUTS3 regions in 2001: in particular, Figure 1 maps NUTS 3 regions which are specialized in creative occupations (i.e. with a value of LQCC bigger than one) while Figure 2 maps the corresponding distribution when using density measures.

3.2. Innovation variables and KPF estimates

In this work, I assess if, and to what extent, the local availability of creative workers has an effect on individual firm innovation intensity. Following the accounting framework developed by Mairesse and Mohnen (2001, 2002) and Mohnen, Mairesse and Dagenais (2006), I rely on two related indicators of innovation ouput. 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 (Mairesse and Mohnen, 2001), and is explained by an explicit econometric model or

[2] According to Cohendet et al. (2010), these groups can be considered as a main driving force for the development of new trends, even if they are not directly linked to the industrial world.

accounting framework, according to a well established empirical literature on the microeconomic determinants of innovation output. Table 2 shows its sample distribution by firm size, area of localization and industry.

The second variable, the one in which I am interested more, 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 viewed like the expected output of innovation activity, as explained by the underlying innovation model adopted, innovativeness is the residual, or the unexplained/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 total factor productivity 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 intensity as function of a series of variables of firm size, sectoral specialization, organizational structure and innovation input, as given by a well developed microeconometric literature on the determinants of innovation activity (Griliches, 1979; Crepon et al., 1998; Mairesse and Mohnen, 2001, 2002; Lööf and Heshmati, 2002; OECD, 2008).

As previously argued, the variable measuring the actual observed innovation intensity is the share of total sales coming from new products[3]. This variable has two shortcomings which make OLS estimates unreliable: first, it is a proportion bounded between 0 and 1; second, it has a left-skewed distribution, with a consistent mass of zeros. In order to tackle these issues, I estimate the KPF in two ways. On the one hand, I follow the standard microeconometric literature on innovation (Crepon et al, 1998; Mairesse and Mohnen, 2001, 2002) and I apply 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 positive observations reduces to 1397. Since not all firms are innovative, and a potential selection bias may arise, I specify the KPF

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

in terms of a generalized Tobit model (or Heckit) 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 for the intensity of innovation, as measured by the logit share of innovative sales.

At this stage, one should note that this approach is suited if we consider all the zeros as structural, which means that they actually correspond to non-innovative firms. However, differently from the CIS case, here I cannot be fully sure of this: while in the CIS the questionnaire is designed in a way to clearly identify a causal sequence between the introduction of new products and the share of innovative sales, in the Unicredit case this last question is posed at the beginning of the questionnaire and it is not directly linked to the Section in which firms are asked about their innovative activities. This fact has two implications: on the one hand, the zero values (56%) cannot be considered as being all structural, but I can reasonably expect that some of them can have an incidental nature; on the other, there are also positive values of innovative sales even for firms that do not record any product innovation in 2004-2006.

In order to account for both the proportional nature of the variable and the point mass at zero, I also estimate a zero-inflated beta regression model (ZIB hereafter), which is commonly applied in empirical papers on consumption and financial economics (Cook at el., 2008). Following Cragg (1971) and Cook et al. (2008), I formulate such a model as follows:

(1) $f(y_i = 0 \mid \mathbf{X}_i) = 1 - C(\alpha' \mathbf{X}_i)$ for $y_i = 0$

(2) $f(y_i \mid \mathbf{X}_i) = C(\alpha' \mathbf{X}_i) \left[\frac{\Gamma(p + q(\mathbf{X}_i))}{\Gamma(p) + \Gamma(q(\mathbf{X}_i)} y_i^{p-1} (1 - y_i)^{q(\mathbf{X}_i)} - 1 \right]$ for $0 < y_i < 1$

where p is the parameter of the beta distribution, $q(\mathbf{X}_i) = p \cdot \exp(-\beta' \mathbf{X}_i)$, C is the probability for a firm to be innovative (i.e. to record positive innovative sales) which I model through a cumulative logistic function, and the term within squared brackets represents the zero-inflated beta probability density, and where the vectors of coefficients α and β are not required to be the same, so that the variables affecting the propensity to innovate can be different from the ones affecting innovation intensity[4].

[4] Other than by theoretical reasons, the choice to use a two-part model against a Tobit one is also confirmed by a non-linear Hausman test for equality of cross-model coefficients (Conte, 2009). Results of the test are available on request.

For both the model specifications, i.e. ZIB and Heckit, I first consider the following variables as regressors in the selection equation, which estimates firm propensity of being innovative[5]: firm size (Size) , as given by the log of average 2004-2006 turnover[6]; 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 Univ/Res), other firms (Coop firm), and other organizations (Coop other), like trade fairs, associations, conferences, showrooms and so on[7]. Finally, I also include 22 two-digit industry-specific dummies in order to control for technological conditions and industry-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, as given by 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 ZIB and Heckit estimates for this basic specification. The residuals of the two outcome equations are then extracted and used for computing firm innovativeness. Figure 3 shows the kernel distribution of innovativeness both in the ZIB (Figure 3a) and in the Heckit (Figure 3b) case; as one can see, the two distributions are approximately Normal, with the former showing a slightly better fit than the

[5] In the ZIB model, the selection equation refers to the probability of generating a value of zero in the dependent variable, instead of a value of one.

[6] Due to the presence of many missing values, I cannot include the traditional variable of average employment. However, the correlation between the two variables is almost 0.5, and significant at 1% level.

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

latter[8]. Table 3, instead, shows its sample distribution according to firm size, NUTS1 area of firms localization and industry.

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 people on firm observed innovative performance, as measured by the actual share of innovative sales. On this purpose, I estimate two main blocks of models, as given in Tables 4 and 5. In the first (columns 1 to 3), I consider the LQ measures of creativity, which I include separately in the OLS estimates due to their strong correlation (higher than 0.8). In the second (columns 4 to 11), I focus on the density measure of creativity, and their squared terms.

For reasons of space, and due to the higher fit with the data, the following comments refer to Table 4 only, where innovativeness comes from the estimate of the ZIB model of the KPF. However, the same results apply to Table 5 and to innovativeness as derived from the Heckit model of the KPF. Having said this, we see from Table 4 that only the local availability of bohemians seems to affect firms actual innovation intensity, even if the effect is rather weak (marginal effect 0.04 and significant at 10%). The other two estimated coefficients, although positive, are not statistically different from zero.

When we look at the density measures, I first find that, when excluding the squared terms, the estimated coefficient is not statistically significant (columns 4, 6, 8 and 10). When I include the squared term, as reported in columns 5, 7, 9 and 11, the coefficients of creativity variables become statistically significant, and identify a U-shaped relationship with innovative sales. In particular, I find that, in order for a positive relationship to emerge, NUTS3 regions should reach a minimum threshold of 47 creative people per squared km, which becomes 16 for graduated creatives, 29 for bohemians, and 23 for university graduates. All these values are largely below the mean level of creativity density, but, due to the generally little size of Italian cities, they concern a bulk of ten provinces only, namely Genoa, Milan, Naples, Rome, Prato, Rimini, Trieste, Varese, Lecco, Como and Padua, eight of them located in the North.

[8] The better fit of the ZIB model is also confirmed by the value of the Spearman rank correlation between the predicted and the actual value of the innovation output variable (Table A1) (Cook et al., 2008).

Interestingly, the threshold level for tertiary educated is higher than the one for graduated creative people (estimates not reported). This means that, in order to have a positive effect on firm innovation intensity, regions should reach a density of at least 23 university graduates, but this threshold becomes lower if these graduates are also employed in a creative job: I interpret this as a sign of a potential additive effect of creativity to education.

4.2. The impact of creativity on firm innovativeness

Tables 6 and 7 show the estimation results for the impact of creativity on firm innovativeness. As before, in the following I will comment results from Table 6 only, since results in Table 7 are on the same line and can be considered as a robustness check.

In order to avoid collinearity problems, I include in the estimates the following controls: three NUTS1 area dummies (North West, North East and South, with Centre being the reference one), two size dummies, one identifying small firms (11-49 employees) and one large firms (more than 250 employees), with medium firms (50-249) being the reference one; one sectoral dummy 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 containing larger urban zones (LUZ), as defined by Urban Audit and Eurostat as enlarged areas including the city and its surroundings (in Italy Milan, Naples, Rome, Palermo, Genoa, Bologna, Florence, Padua, Verona, Venice, Turin, Messina, Catania, Trieste, Cagliari and Bari).

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 0.15 percentage points. Interestingly, I also find that the impact of bohemians (0.17) is higher than the one of graduated creative workers (0.09).

With respect to density measures, results confirm that, when the squared terms are excluded, the estimated coefficient is never statistically different from zero. When I include them, instead, I find the presence of a strong nonlinear effect: in particular, now NUTS3 regions should reach a minimum threshold of 53 creative people per squared km, 19 qualified creatives, 40 bohemians, and 27 university graduates in order to make manufacturing firms to increase their innovativeness. Differently from before, now all these values are much closer to

the corresponding mean levels: this suggests that only firms located in a small number of cities (namely the larger urban zones) can benefit from creativity spillovers[9].

Summing up, positive knowledge externalities in the form of creativity spillovers on firm innovativeness seem to emerge only in large urban contexts and seem to be higher for bohemians than for graduated creative workers. This puzzling result can find many different explanations. The first is that creative people have not necessarily to be also highly educated (Florida, 2002a, Marlet and van Woerkens, 2007, Andersson, 2011). In other words "[i]it'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 creative economy, as primarily driven by high-quality craft-based productions located in small municipalities (Bertacchini and Borrione, 2012).

Third, the effect of graduated creative people can be partly included in the estimated coefficient of R&D labour in the KPF. If, as reasonably expected, creative people with a university degree are engaged in formal intra- and extra-mural R&D activities, then there can be a potential double-counting effect on this variable[10] which lowers its coefficient.

Finally, another plausible explanation is that the local availability of graduated creative people does affect more the inventive, or patenting, activity of firms, rather than their (expected or unexpected) 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 case and by Boschma and Fritsch (2009) for European countries, whereas little or no evidence is available for Italy.

I then try to test for this hypothesis by looking at the relationship between creativity and the number of per-capita inventions within Italian provinces. Since I do not have firm-level information on patents, I rely on NUTS3 level data on inventions provided by Istat for

[9] With respect to the actual innovative share case, now the range of cities is limited to Milan, Naples, Prato, Rimini, Trieste, Rome and Varese, most of which host service-based creative industries.

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

the period 2001-2003; therefore, as dependent variable, I consider the number of inventions (patents, trademarks and prototypes) registered at the European Patent Office 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 in 2000 and the log of population density in 2001, in order to control for income and urbanization effects. Results from standard OLS estimates are presented in Table 8[11]. As expected, I find that the rate of invention is affected only by the relative share of graduated creative workers, whereas Bohemians do not seem to play any relevant effect[12].

This result is, thus, in line with the idea that the most qualified creative workers are 'repository' of technological creativity, whereas less qualified ones are more related to the concept of economic creativity and to the creation and development of business-related activities (UNCTAD, 2008)[13]. 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".

4.3. Endogeneity and nonlinearity

As typical in agglomeration studies, the relationship between innovation output and creativity can be endogenous. Such endogeneity can basically arise because of: (i) simultaneity between the dependent variable and the covariates; (ii) unobserved factors which affect innovation output and are not related to creativity. I overcome the first problem by considering a five years time lag between innovation output and creativity measures, the former being measured in 2006 and the latter in 2001.

[11] I also control for potential endogeneity bias through a 2SLS procedure. See Section 4.3 for details.

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

[13] 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%), followed by a primary school degree (32%) and by a tertiary degree (22%).

With respect to the second source of endogeneity, I first saturate the estimates of both the KPF and the innovativeness function with controls on size, industry and other firm activities. Second, I re-estimate the two models with a two-stage least squares (2SLS) procedure, in which, as instrument, I use an amenity-based index for each NUTS3 region, as given by the number of art galleries, museums, libraries and tourists per inhabitant in 2001. In so doing, following Florida (2002a), Marlet and van Woerkens (2007), Wojan and McGranahan (2007), Florida et al. (2008) and Mellander and Florida (2011), I assume that talents are attracted not only, or not much, by high-income cities[14], but also by 'culturally attractive' cities, with a high degree of openness, diversity and tolerance[15] (UNCTAD, 2010; Simonton, 2011).

For each 2SLS estimate, I then compute the corresponding endogeneity test, which, in the case of a cluster-robust variance-covariance matrix, is given by the Wooldridge (1995) robust score test. Results of these tests are reported in the last row of Tables 5, 6 and 7[16]. In all the cases, the null hypothesis of exogeneity cannot be rejected, so that OLS estimates can be taken as consistent.

As explained in Section 2, a second issue that typically characterizes the studies on urban increasing returns concerns the presence of nonlinearities. Again, nonlinearities can take two forms. On the one hand, the presence of 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 certain density threshold is reached; in this case, the relationship between creativity and innovation becomes U-shaped.

[14] Income *per sè* cannot also be a good instrument as it would correlate with innovation output (Johansson and Lööf, 2009).

[15] As a robustness check, instead of the amenity-based index, I use the Tolerance index, as developed by Florida and Tinagli (2005), as instrument in the 2SLS estimates. As expected, results do not change.

[16] Results for the density measures of creativity in Tables 6 and 7 are not reported for reasons of space, but are in line with the ones for the LQ measures. For what concerns the KPF estimates, I only test the endogeneity of creativity in the Heckit model (Table 5), where I run a standard OLS estimate on the restricted sample of innovative firms only, and where 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.

In order to test for the presence of nonlinear effects, I first introduce in the OLS estimates the squared terms of the density variables[17], as reported in Tables 4 to 7. Then, I also test for the strength of these nonlinearities by separately estimating a set of generalised additive (or proportional hazard) models (GAM) of innovation intensity (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 for both the ZIB and the Heckit case are shown in Table 9. Looking at the magnitude of the gain statistic and to its level of significance, it is clear that the 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 between the density of creative workers and actual innovative sales is weak, as also confirmed by Figure 4, where the grey area identified by the 5% confidence intervals is rather ample. Figure 5, instead, shows the U-shaped relationship between innovativeness and the (log) density of creativity: in line with Table 9, now we can really argue that positive knowledge spillovers from proximity to creative workers emerge only after a certain density threshold is reached.

These results can have a double interpretation. On the one hand, it can be the case that only after a certain density is reached, firms and creative workers are able to minimize their mutual search and job matching costs. On the other, following Jacobs (1969) and Currid (2007), 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 tyoes of music, fashion, and art" (Currid, 2007, p. 91).

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

5. Conclusions and policy implications

In this paper I try to identify the presence 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 terms, the higher the local availability of creative workers, the higher the innovation intensity of firms. This effect is particularly true when we look at the unexplained part of the innovation output, namely innovativeness, rather than at the actual, observed, share of innovative sales. Moreover, when I control for the level of qualification of creative workers, I find that innovativeness is more affected by the local availability of the medium-qualified ones, whereas attracting highly qualified creative people seems to affect the initial part of the innovation process, namely the invention rate.

Interestingly, when I measure creativity through a standard education-based indicator, estimated coefficients have the same level of significance, but are always lower than the previous ones. Therefore, in this case standard measures of human capital tend to underestimate the impact of creativity on firm innovative performance.

The existence of knowledge spillovers is also confirmed when I measure creativity in terms of density. In this case, a U-shaped relationship seems to characterize creativity and firm innovativeness, so that positive externalities emerge only after a certain density threshold is reached, which occurs when the province includes a large urban area.

From the policy point of view, increasing the availability of creative jobs and people can help regions and cities to be more innovative, 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. However, in order for proximity-based knowledge externalities to emerge in the process of exploration and exploitation of new ideas, cities have to be 'large' enough: in this sense, a potential selection effect on larger, and more urbanized, areas may emerge, in line, for instance, with Andersen et al. (2011), who find support at the North Europe level to Richard Florida's thesis, according to which the effect of the creative class on regional economic development are like to show in larger city regions. Put it another way, only cities can provide the chances, and the institutions, for making creative workers to meet, to exchange ideas, and to 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 (Crepon et al., 1998), then, in the absence of estimated congestion effects, a

virtuous circle starting from creativity and ending on firm production performance can also emerge, in the spirit of the endogenous growth theory (Lucas, 1988).

References

Andersen, K.V., Hansen, H.K., Isaksen, A., Raunio, M. (2011), Nordic city regions in the creative class debate – Putting the creative class thesis to a test, *Industry and Innovation* 17, 215-240.

Andersson, A.E. (2011), Creative people need creative cities, in Andersson, E. et al. (Eds.), *Handbook of creative cities,* Cheltenham, Edward Elgar.

Andersson, E., Andersson, A.E., Mellander, C. (2011), *Handbook of creative cities,* Cheltenham, Edward Elgar.

Atkinson, R., Easthope, H. (2009), The consequences of the creative class: the pursuit of creativity strategies in Australia's cities, *International Journal of Urban and Regional Research* 33, 64-79.

Bertacchini, E.E., Borrione, P. (2012), The geography of the Italian creative economy: the special role of the design and craft-based industries, *Regional Stuides*, DOI: 10.1080/00343404.2011.628625.

Black, S.E., Lynch, L.M. (1996), Human capital investment and productivity, *American Economic Review* 86, 263-267.

Boschma, R.A., Fritsch, M. (2009), Creative class and regional growth: empirical evidence from seven European countries, *Economic Geography* 85(4), 391-423.

Carlino, G.A., Chatterjee, S., Hunt, R.M. (2007), Urban density and the rate of invention, *Journal of Urban Economics* 61, 389-419.

Ciriaci, D. (2011), Design and European firms' innovative performance: evidence from European CIS non anonymous data, IPTS Working Paper on Corporate R&D and Innovation 08/2011.

Cohendet, P., Grandadam, D., Simon, L. (2010), The anatomy of the creative city, *Industry and Innovation* 17, 91-111.

Conte, A. (2009), Mapping innovative activity using microdata, *Applied Economic Letters* 16, 1795-1799.

Cook, D.O., Kieschnick, R., McCullough, B.D. (2008), Regression analysis of proportions in finance with self selection, *Journal of Empirical Finance* 15, 860-867.

Cragg, J. (1971), Some statistical models for limited dependent variables with application to the demand for durable goods, *Econometrica* 39, 829-844.

Crepon, B., Duguet, E., Mairesse, J. (1998), Research, innovation and productivity: an econometric analysis at the firm level, *Economics of Innovation and New Technology* 7, 115-158.

Currid, E. (2007), The Warhol economy. How fashion, art & music drive New York city, Princeton, Princeton University Press.

Florida, R. (2002a), *The rise of the creative class*, New York, Basic Books.

Florida, R. (2002b), The economic geography of talent, *Annals of the Association of American geographers* 92, 743-755.

Florida, R. (2002c), Bohemia and economic geography, *Journal of Economic Geography* 2, 55-71.

Florida, R., Tinagli, I. (2005), Italy in the creative age, Creativity Group Europe.

Florida, R., Mellander, C., Stolarick, K. (2008), Inside the black box of regional development – human capital, the creative class and tolerance, *Journal of Economic Geography* 8, 615-649.

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

Griliches, Z. (1979), Issues in assessing the contribution of research and development to productivity growth, *The Bell Journal of Economics* 10, 92-116.

Hastie, T.J., Tibshivani, R. (1990), *Generalized additive models*, London, Chapman and Hill.

Hollanders, H., Van Cruysen, A.(2009), Design, creativity and innovation: a scoreboard approach, European Innovation Scoreboard 2008, European Commission.

Istat (2001), XIV Censimento generale della popolazione e delle abitazioni, Istat, Rome.

Istat (2006), Le nuove attività imprenditoriali, Istat, Rome.

Jacobs, J. (1969), The economy of cities, New York, Vintage Books.

Johansson, B., Lööf, H. (2009), Innovation, R&D and productivity. Assessing alternative specifications of CDM-models, CESIS Working Paper 159.

Lee, Y.S., Florida, R., Acs, Z. (2004), Creativity and entrepreneurship: a regional analysis of new firm formation, *Regional Studies*, 38, 879-891.

Lööf, H., Heshmati, A. (2002), Knowledge capital and performance heterogeneity: a firm-level innovation study, *International Journal of Production Economics* 76, 61-85.

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

Mairesse, J.**,** Mohnen, P. (2001), To be or not to be innovative: an exercise in measurement, NBER Working Paper 8644.

Mairesse, J.**,** Mohnen, P. (2002), Accounting for innovation and measuring innovativeness: an illustrative framework and an application, *American Economic Review* 92(2), 226-230.

Mairesse, J.**,** Mohnen, P. (2010), Using innovation surveys for econometric analysis, in Hall, B.H., Rosenberg, N. (Eds.), *Handbook of the economics of innovation*, North Holland, vol. 2, chapter 26.

Mairesse, J.**,** Mohnen, P., Dagenais, M. (2006), Innovativity: a comparison across seven European countries, *Economics of Innovation and New Technology* 15, 391-413.

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

Marlet, G., van Woerkens, C. (2007), The Dutch creative class and how it fosters urban employment growth, *Urban Studies* 44, 2605-2626.

Marrocu, E., Paci, R. (2011), Education or creativity: what matters most for economic performance?, CRENOS Working Paper 2010/31.

Mcgranahan, D., Wojan, T. (2007), Recasting the creative class to examine growth processes in rural and urban counties, *Regional Studies* 41, 197-216.

Mellander, C., Florida, R. (2011), Creativity, talent, and regional wages in Sweden, *Annals of Regional Science* 46, 637-660.

Miles, I., Green, L. (2010), Innovation and creative services, in Gallouj, F., Djellal, F. (Eds.), The handbook of innovation and services, Cheltenham, Edward Elgar, pp. 178-196.

Moretti, E. (2004a), Workers' education, spillovers, and productivity: evidence from plant-level production functions, *American Economic Review* 94, 656-690.

Moretti, E. (2004b), Human capital externalities in cities, in Henderson, J.V., Thisse, F. (Eds.), *Handbook of regional and urban economics*, North Holland, 4, 2243-2291.

Nathan, M. (2007), The wrong stuff? Creative class theory and economic performance in UK cities, *Canadian Journal of Regional Science* 30, 433-450.

OECD (2008), OECD Science, technology and industry outlook, OECD, Paris, Chapter 5.

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

Simonton, D.K. (2011), Big-C creativity in the big city, in Andersson, E. et al. (Eds.), *Handbook of creative cities*, Cheltenham, Edward Elgar.

Sternberg, R.J. (2006), Introduction, in Kaufman, J.C., Sternberg, R.J. (Eds.), *The international handbook of creativity*, Cambridge, Cambridge University Press, 1-10.

UNCTAD (2010), Creative economy report 2010, UNDP, Geneva and UNCTAD, New York.

Villalba, E. (2008), On creativity, JRC Scientific and Technical Report, European Commission.

Wojan, T.R., McGranahan, D.A. (2007), Ambient returns: creative capital's contribution to local manufacturing competitiveness, *Agricultural and Resource Economics Review,* 36, 133-148.

Wooldridge, J.M. (1995), Score diagnostics for linear models estimated by two stage least squares, in Maddala, G.S., Phillips, P.C.B., Srinivasan, T.N. (Eds.), *Advances in econometrics and quantitative economics: essays in honour of Professor C.R. Rao*, Oxford, Blackwell, 66-87.

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
Large Urban Zone (LUZ)	11.42	25.27
Non LUZ	11.26	26.16
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
Medium-low + low-tech	13.69	25.76
Medium-high + high tech	10.29	26.07
Average %	11.31	25.88
Num. obs.	3197	1397

Table 3. Average innovativeness by size, area and industry

Size	**ZIB**	**Heckit**
11-20	0.980	2.058
21-50	1.010	1.813
51-250	1.043	1.595
251-500	1.058	1.315
> 500	1.096	1.169
Area		
North West	1.023	1.761
North East	1.015	1.653
Centre	0.989	1.878
South	1.024	1.685
Metropolitan city	1.022	1.734
Non-metropolitan city	1.012	1.744
Pavitt		
Suppl. Dominated	0.984	1.830
Scale intensive	1.039	2.086
Special. Suppliers	1.034	1.491
Science based	1.132	1.477
Medium-low + low-tech	1.011	1.881
Medium-high + high tech	1.024	1.489
Average	1.015	1.741
Num. obs.	3197	1397

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

ZIB	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LQ(CC)	0.241										
	(0.221)										
LQ(QCR)		0.099									
		(0.139)									
LQ(Bohemians)			0.478*								
			(0.243)								
Marginal effect			[0.042]								
Log(DenCC)				0.004	-0.407**						
				(0.028)	(0.168)						
$Log(DenCC)^2$					0.053**						
					(0.021)						
Log(DenQCR)						0.002	-0.282**				
						(0.027)	(0.118)				
$Log(DenQCR)^2$							0.051**				
							(0.020)				
Log(DenBohemians)								0.005	-0.363**		
								(0.028)	(0.152)		
$Log(DenBohemians)^2$									0.054**		
									(0.022)		
Log(DenEDU)										0.003	-0.300**
										(0.027)	(0.129)
$Log(DenEDU)^2$											0.048**
											(0.020)
N	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197

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

Table 5. Knowledge production function estimates: impact of creativity measures on the actual logit share of innovative sales

Heckit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LQ(CC)	0.341										
	(0.320)										
LQ(GCR)		0.202									
		(0.202)									
LQ(NGCR)			0.736**								
			(0.337)								
Log(DenCC)				0.037	-0.406**						
				(0.035)	(0.162)						
$Log(DenCC)^2$					0.058***						
					(0.020)						
Log(DenQCR)						0.035	-0.280**				
						(0.034)	(0.109)				
$Log(DenQCR)^2$							0.056***				
							(0.018)				
Log(DenBohemians)								0.038	-0.356**		
								(0.035)	(0.150)		
$Log(DenBohemians)^2$									0.058***		
									(0.020)		
Log(DenEDU)										0.036	-0.298**
										(0.033)	(0.121)
$Log(DenEDU)^2$											0.053***
											(0.018)
N	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197	3197
Uncensored	1397	1397	1397	1397	1397	1397	1397	1397	1397	1397	1397
Endogeneity test	0.025	0.091	0.005	0.247		0.269		0.237		0.244	
(p-value)	(0.874)	(0.764)	(0.942)	(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%.

Table 6. The impact of creativity on innovativeness: OLS estimates

ZIB	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LQ(CC)	0.151**						
	(0.061)						
LQ(GCR)		0.089**					
		(0.044)					
LQ(NGCR)			0.171**				
			(0.080)				
Log(DenCC)				-0.183***			
				(0.038)			
$Log(DenCC)^2$				0.023***			
				(0.005)			
Log(DenQCR)					-0.123***		
					(0.026)		
$Log(DenQCR)^2$					0.021***		
					(0.005)		
Log(DenBohemians)						-0.170***	
						(0.031)	
$Log(DenBohemians)^2$						0.023***	
						(0.004)	
Log(DenEDU)							-0.138***
							(0.043)
$Log(DenEDU)^2$							0.021***
							(0.005)
N	3197	3197	3197	3197	3197	3197	3197
R^2	0.12	0.12	0.12	0.19	0.19	0.19	0.19
Endogeneity test	0.064	0.093	0.096				
(p-value)	(0.801)	(0.761)	(0.757)				

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%.

Table 7. The impact of creativity on innovativeness: OLS estimates

Heckit	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LQ(CC)	1.028**						
	(0.509)						
LQ(GCR)		0.560					
		(0.409)					
LQ(NGCR)			1.413*				
			(0.729)				
Log(DenCC)				-0.930***			
				(0.275)			
$Log(DenCC)^2$				0.124***			
				(0.034)			
Log(DenQCR)					-0.600***		
					(0.163)		
$Log(DenQCR)^2$					0.112***		
					(0.163)		
Log(DenBohemians)						-0.866***	
						(0.228)	
$Log(DenBohemians)^2$						0.130***	
						(0.033)	
Log(DenEDU)							-0.665***
							(0.249)
$Log(DenEDU)^2$							0.110***
							(0.037)
N	1397	1397	1397	1397	1397	1397	1397
R^2	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Endogeneity test	0.264	0.386	0.214				
(p-value)	(0.609)	(0.536)	(0.645)				

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%.

Table 8. The impact of creativity on invention: OLS estimates

Variables	(1)	(2)	(3)
Log(VA)	2.297***		
	(0.397)		
Log(Density)	0.789***		
	(0.150)		
LQ(CC)	2.905**		
	(1.150)		
R^2	0.502		
LQ(QCR)		2.406***	
		(0.831)	
R^2		0.525	
LQ(Bohemians)			0.857
			(1.690)
R^2			0.471
Num. obs.	103	103	103

Notes: heteroskedasticity-robust standard errors in brackets. All the estimates also include a constant term. Dependent variable is the 2001-2003 average inventions (patents, trademarks, prototypes) per million of inhabitants registered at the European Patent Office (natural log).

Table 9. Generalized additive model estimates on creativity density

Density variables	**Innovative sales (ZIB)**	**Innovative sales (Heckit)**
Log(DenCC)	1.972 (0.161)	3.417 (0.065)
Log(DenQCR)	3.052 (0.081)	3.589 (0.059)
Log(DenBohemians)	1.466 (0.226)	3.229 (0.072)
Log(DenEDU)	2.503 (0.114)	3.162 (0.076)
	Innovativeness (ZIB)	**Innovativeness (Heckit)**
Log(DenCC)	25.709 (0.000)	9.783 (0.002)
Log(DenQCR)	27.909 (0.000)	8.836 (0.003)
Log(DenBohemians)	28.982 (0.000)	10.227 (0.001)
Log(DenEDU)	29.097 (0.000)	8.714 (0.003)

Notes: p-values in brackets.

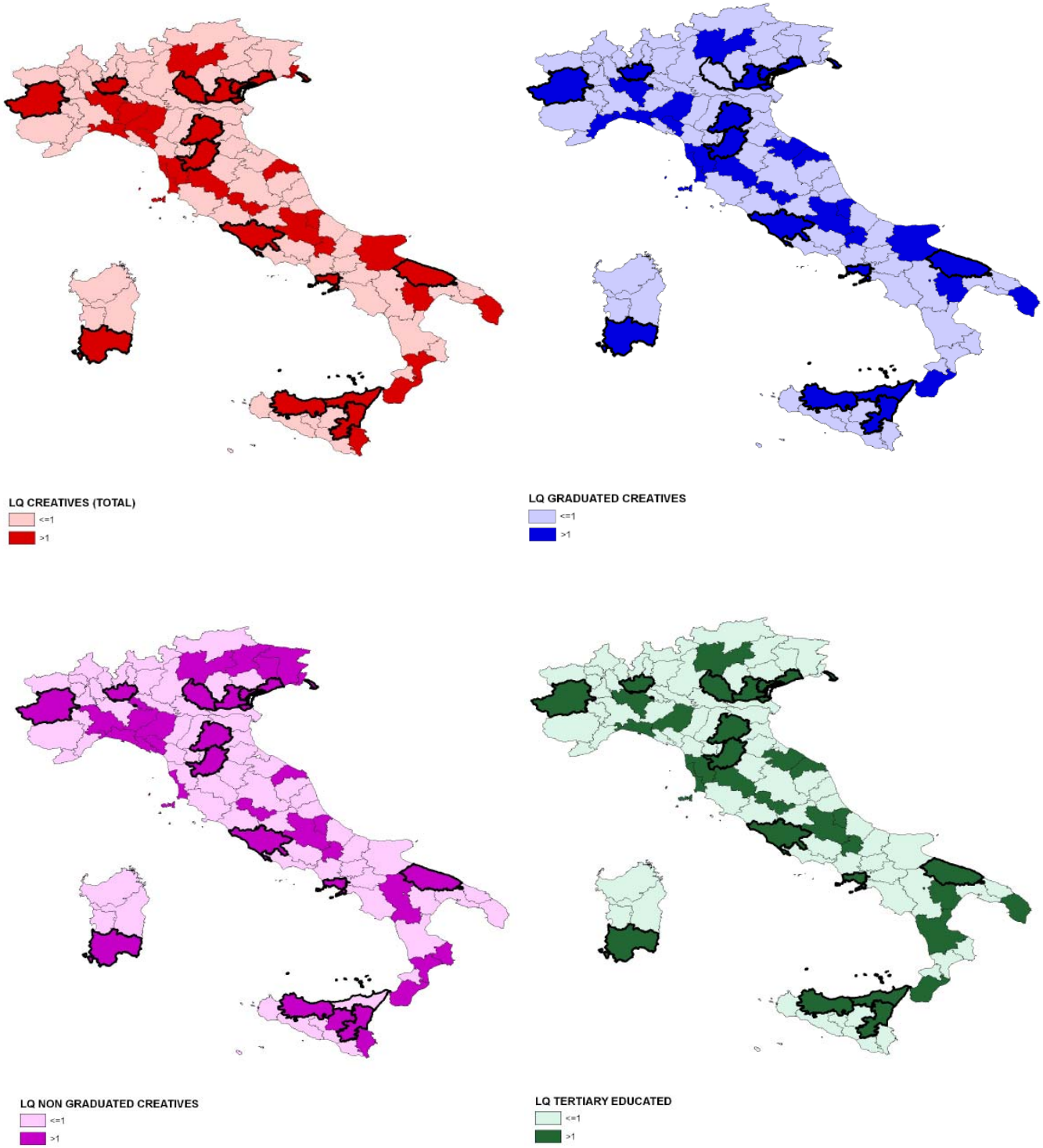
Appendix

Table A1. Knowledge production function estimates: basic specification

	ZIB		Heckit	
	Zero inflate	**Proportion**	**Selection**	**Outcome**
Group	-0.062	0.032	-0.016	-0.087
	(0.102)	(0.073)	(0.048)	(0.119)
Consortium	0.544***	0.120	0.304***	0.691***
	(0.201)	(0.115)	(0.104)	(0.233)
Size	0.219***	-0.031	0.133***	0.145***
	(0.032)	(0.023)	(0.017)	(0.046)
Export	0.431***	-0.094	0.237***	0.303***
	(0.086)	(0.062)	(0.055)	(0.115)
Tax Reliefs	0.359***		0.087**	
	(0.096)		(0.044)	
Coop Univ/Res	0.456**	-0.311***	0.221*	-0.088
	(0.186)	(0.091)	(0.124)	(0.221)
Coop Firm	-0.033	0.145	0.050	0.118
	(0.304)	(0.243)	(0.190)	(0.442)
Coop Other	1.033***	-0.079	0.534***	0.711***
	(0.096)	(0.083)	(0.082)	(0.167)
R&D labour		0.832***		0.876***
		(0.186)		(0.233)
Process innovation		0.163***		0.221***
		(0.053)		(0.065)
Ln Input		0.170		0.394*
		(0.160)		(0.227)
Ln ICT		0.711		1.181
		(0.624)		(1.003)
Industry dummies	Yes	Yes	Yes	Yes
Num. obs.	3197	1397	3197	1397
Log pseudo LL	-1604.453		-4466.43	
Log (phi)	1.055***			
Lambda			2.118***	
Spearman rank corr.		0.2092***		0.1730***

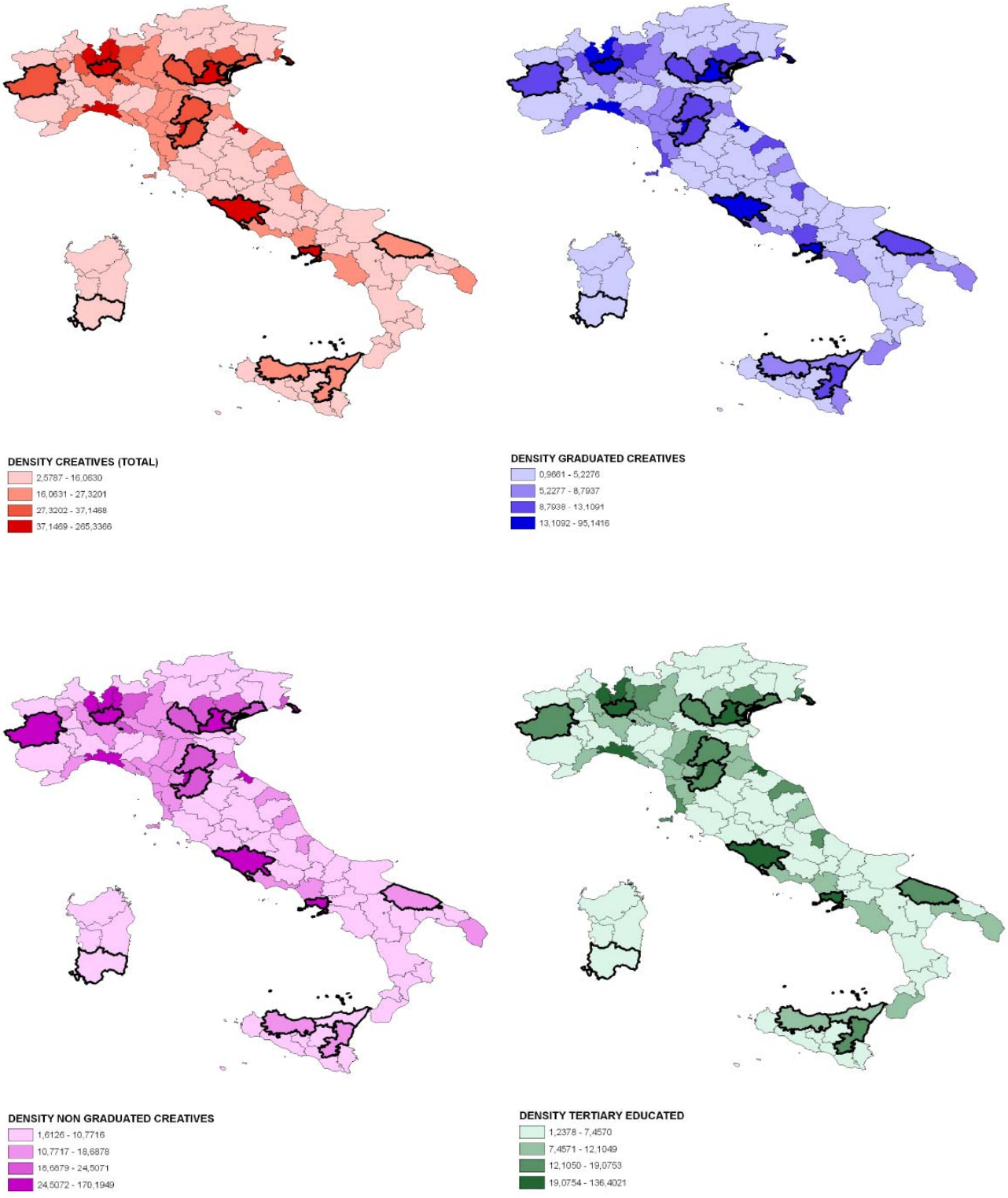
Notes: rows report estimated coefficients of the regressors, not marginal effects NUTS3 region-level clustered-robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The signs of the estimated coefficients of the zero-inflate beta model refer to the probability to determine a positive count, instead of a zero value.

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



Source: Census of Population (Istat, 2001). Thicker borders refer to NUTS3 regions including larger urban zones (LUZ).

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



Source: Census of Population (Istat, 2001). Thicker borders refer to NUTS3 regions including larger urban zones (LUZ).

Figure 3. Kernel distribution of innovativeness

(a) ZIB **(b) Heckit**

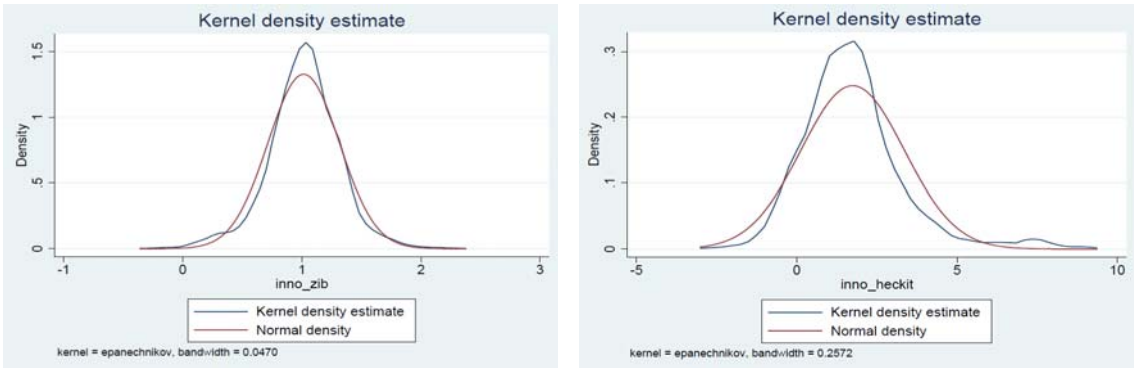


Figure 4. Innovative sales and (log) creative class density

(a) ZIB **(b) Heckit**

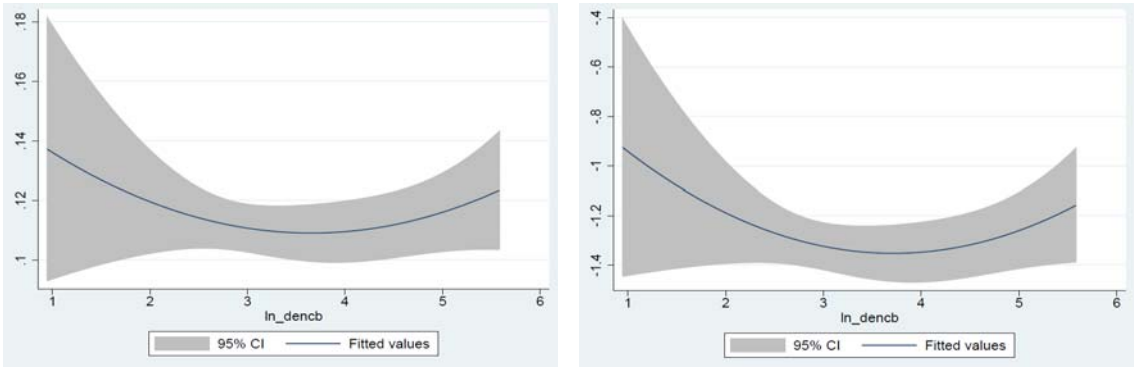


Figure 5. Innovativeness and (log) creative class density

(a) ZIB **(b) Heckit**