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University knowledge and the creation of innovative start-ups: An analysis of the Italian case

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Abstract

Grounding on the Knowledge Spillover Theory of Entrepreneurship, this paper studies whether and how university knowledge affects the creation of innovative start-ups at the local level. First, we assess the impact of university knowledge on the creation of innovative start-ups in a geographical area by distinguishing between university knowledge, which is produced inside and outside the boundaries of the focal area. Second, we discuss and empirically investigate whether open-minded attitudes of individuals that reside in the area favor the exploitation of geographically distant university knowledge for the creation of innovative start-ups. Results from estimations of zero inflated negative binomial regressions on a sample of 792 province-industry pairs show that university knowledge stimulates the creation of innovative start-ups at the local level. However, this positive effect holds only when considering university knowledge created inside the boundaries of the focal area. Interesting enough, university knowledge created outside the boundaries of the focal area affects the creation of innovative start-ups only where individuals have high open-minded attitudes.

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Keywords: University knowledge, young innovative companies, innovative start-ups, geographical distance, open-minded individuals.

Abstract

Grounding on the Knowledge Spillover Theory of Entrepreneurship, this paper studies whether and how university knowledge affects the creation of innovative start-ups at the local level. First, we assess the impact of university knowledge on the creation of innovative start-ups in a geographical area by distinguishing between university knowledge, which is produced inside and outside the boundaries of the focal area. Second, we discuss and empirically investigate whether open-minded attitudes of individuals that reside in the area favor the exploitation of geographically distant university knowledge for the creation of innovative start-ups. Results from estimations of zero inflated negative binomial regressions on a sample of 792 province-industry pairs show that university knowledge stimulates the creation of innovative start-ups at the local level. However, this positive effect holds only when considering university knowledge created inside the boundaries of the focal area. Interesting enough, university knowledge created outside the boundaries of the focal area affects the creation of innovative start-ups only where individuals have high open-minded attitudes.

1. Introduction

Young Innovative Companies (YICs) have recently attracted increasing attention by scholars and policymakers (Veugelers 2008; Audretsch et al. 2014; EC-DG ENTR. 2009). YICs are typically small, young companies, intensively engaged in innovation activities (see Czarnitzki and Delanote 2013 for a detailed description). What distinguish YICs from innovating SMEs is their superior ability to generate new knowledge or combine existing knowledge to create innovations that are not only new to the firm, but also new to the market (Veugelers 2008). As noted by Schneider and Veugelers (2010, p. 972), YICs can "develop important innovations with significant potential commercial applications and social value". In other words, YICs tend to introduce more radical innovations than incumbents do, as they are more flexible and less concerned with safeguarding their existing competences. Empirical studies have shown that YICs' performance are higher than those of other firms are. Relying on a sample of German YICs, Schneider and Veugelers (2010) have found that sales related to innovative products are significantly higher for these firms than for other innovation-active firms. In a similar vein, a study by Czarnitzki and Delanote (2013) investigating the YICs in Flanders, has demonstrated that YICs grow faster than other firms, and this result holds when measuring growth both in terms of sales and in terms of employment.

From the discussion above, it appears clear that the emerging literature on YICs has mainly focused on the innovation activities and performance of these firms. Conversely, we know comparatively less on the factors that hamper or facilitate their creation. Specifically, little is known on what drives the creation of new YICs, i.e. the creation of innovative start-ups. In a recent study, Fritsch and Aamoucke (2013) have found that knowledge produced by academic research (hereafter: university knowledge) has a positive impact on the creation of new firms in innovative industries[1]

[1] The authors include on their analysis German firms in (i) high-technology manufacturing industries, devoting more than 8.5 % of their input to R&D; (ii) technologically advanced manufacturing industries (R&D intensity between 3.5 and 8.5 %); and (iii) technology-oriented services, covering only some selected service industries related to innovation and new technology.

despite the fact that this effect is highly localized. However, as most empirical studies in the field (e.g., Audretsch and Lehmann 2005; Baptista and Mendonça 2010; Bonaccorsi et al. 2014a), the authors do not consider explicitly the creation of innovative start-ups, but "include all start-ups in innovative and knowledge-intensive industries" (Fritsch and Aamoucke 2013, p. 866), therefore using a definition at the industry- rather than at the firm-level. Moreover, whilst acknowledging the importance of university knowledge, they do not consider that local factors may foster or hamper the exploitation of this knowledge for the creation of innovative start-ups.

This paper moves a further step in this direction. Specifically, building on the Knowledge Spillover Theory of Entrepreneurship (KSTE, Acs et al. 2013; Acs et al. 2009), we discuss and empirically investigate how university knowledge fosters the creation of innovative start-ups at the local level. First, we assess the impact of university knowledge on the creation of innovative start-ups in a geographical area by distinguishing between university knowledge, which is produced inside and outside the boundaries of the focal area. Second, and more interestingly, we study whether the characteristics of the individuals that reside in the area favour the exploitation of distant university knowledge. For sake of relevance, we focus on individuals' open-minded attitudes. Indeed, the literature has shown that open-minded individuals are better able to exploit innovative entrepreneurial opportunities (McCrae 1987; Dyer et al. 2008) and to re-combine knowledge to create radical innovations that are the basis for the creation of innovative start-ups (Ward et al. 1997; Poel 2003).

In the empirical part of the paper, we estimate a series of zero-inflated negative binomial regressions. The dependent variable is the number of innovative start-ups belonging to 8 industries (according to the NACE rev. 2 classification) created in 99 Italian provinces between 2011 and 2014, leading to a sample of 792 province-industry pairs (see Glaeser and Kerr 2009 and Ghani et al. 2013 for similar approaches). The Italian provinces refer to the NUTS3 level of the European classification of geographical areas.[2] The main explanatory variables refer to knowledge produced by universities within and outside a focal province (see Bonaccorsi et al. 2014a for a similar approach) and to the level of integration between Italian and foreign-born population, which we use as a proxy of the open-minded attitudes of individuals residing in that province (Florida and Tinagli 2005).

The paper advances received knowledge in several respects. First, it contributes to the emerging literature on YICs by acknowledging the strong linkages between the creation of these firms at the local level and the university system. Second, it adds to the research stream on KSTE, which has just started to investigate the role of local factors in weakening or magnifying the effect of knowledge spillovers on entrepreneurship (Qian and Acs 2013; Qian et al. 2013). Finally, our work re-asserts the centrality of individuals and of individual attitudes in the entrepreneurship field.

The paper proceeds as follows. The next section provides the theoretical background and develops the research hypotheses. Section 3 describes the econometric models used to test these hypotheses and the dependent and independent variables included in the models. In section 4, we illustrate the results of the econometric analysis. Section 5 concludes.

2. Theoretical background and hypotheses development

The impact of university knowledge on the creation of new firms has been receiving a growing attention by scholars within the research stream of KSTE (Acs et al. 2009; see Ghio el al. 2014 for a recent survey of this emerging literature). According to KSTE, new firm creation is an effective mechanism through which knowledge generated by universities is transferred to the productive system (Audretsch and Lehmann 2005). With respect to incumbent firms, perspective entrepreneurs are indeed better able to overcome the knowledge filter (Acs and Plummer 2005; Acs et al. 2009),

[2] The Nomenclature of territorial units for statistics (NUTS) classification is a hierarchical system for dividing the European economic territory. The current NUTS classification valid from 1 January 2012 until 31 December 2014 lists 97 regions at NUTS-1, 270 regions at NUTS-2 and 1294 regions at NUTS-3 level. For further information see http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction.

which typically limits the conversion of university knowledge into commercial knowledge. In particular, knowledge generated by universities and spilling over from its source is often not immediately usable for the development of commercial products and services (Bercovitz and Feldman 2006; Carlsson et al. 2009; Bonaccorsi et al. 2014a). To the extent that incumbent firms do not exploit university knowledge, as they prefer to stick on their existing skills and competences, it generates entrepreneurial opportunities, which prospective entrepreneurs may thus exploit through new firm creation.

Along this line of reasoning, we maintain that university knowledge is of paramount importance for the creation of innovative start-ups (i.e., new YICs). Indeed, university knowledge is often radical as it results from scientists' race to achieve first a discovery or to solve first a complex scientific and technical problem (see e.g., Stephan 2012). The availability of radical knowledge is an important input for the development of the radical innovations (Freeman 1992; Poel 2003; Schoenmakers and Duysters 2010) on which YICs base their competitive advantage. Accordingly, one can reasonably expect that perspective entrepreneurs intending to create an innovative start-up in a geographical area would largely benefit from the local availability of university knowledge. Therefore, our first hypothesis states as follows.

H1: Local availability of university knowledge positively affects the creation of innovative start-ups in a geographical area.

However, universities are unevenly located across territories. Consequently, despite the public good nature of university knowledge, its availability is not geographically uniform (Döring and Schnellenbach 2006). Starting from the seminal work of Jaffe (1989), many studies conducted in both the US and Europe have documented that the effects of university knowledge on industrial innovation activities decrease with the distance from the university generating the knowledge (e.g., Anselin et al. 1997; Anselin et al. 2000; Audretsch and Feldman 1996; Jaffe 1989; Fischer and Varga 2003).

More recently, several contributions have provided evidence of a positive relationship between localized university knowledge spillovers and local entrepreneurship (see among the others, Audretsch and Lehmann 2005; Bonaccorsi et al. 2013; Acosta et al. 2011). In sum, scholars concur that universities mainly influence the productive system of the local context in which they are sited. The explanation of this phenomenon is straightforward. University knowledge is hardly understandable by non-academics, who must interact with academics to fully appreciate the potentialities of this knowledge. As geographical proximity favors direct interactions (Lundvall 1988; Gertler 2003) between academic personnel and business people, it likely facilitates the commercial exploitation of university knowledge.

Moving from these premises, we argue that the highly localized nature of university knowledge spillovers holds particularly true when considering the creation of innovative start-ups. Indeed, a perspective entrepreneur intending to create an innovative start-up out of radical university knowledge must transform this knowledge into new products and services. Such process is particularly troublesome as radical knowledge has a high cognitive complexity and a large tacit component (Antonelli 2011) and it is thus sticky (Pavitt 1991). In such a context, direct contacts between academic personnel and perspective entrepreneurs turn out to be of fundamental importance as they favour the absorption of radical knowledge through interactive learning (Autio et al. 2004). The fact that academics codify radical university knowledge into scientific publications is often not enough to allow non-academics to understand it. Scientists have developed specialized languages, with specific codes and meanings, which are hardly understandable by outsiders (Gardner 2004; Halliday and Martin 1993). Along this line of reasoning, a recent contribution by Bonaccorsi et al. (2014a) distinguishes local university knowledge (i.e., knowledge created by universities located in a given geographical area) from the external university knowledge (i.e., knowledge created by universities located outside the area). The authors find that the positive effect of scientific publications on the creation of new firms in high-tech industries is confined within the boundaries of the province where universities are located. Expanding on these insights, we put forth hypothesis H2.

H2: External university knowledge does not affect the creation of innovative start-ups in a geographical area.

However, we argue that the characteristics of the individuals residing in a geographical area may reduce the barriers hampering the absorption of external university knowledge, thus favoring its exploitation for the creation of innovative start-ups. Recent developments within the KSTE framework have pointed to the concept of the entrepreneurial absorptive capacity (EAC, Qian and Acs 2013), defined as individuals' ability to understand new knowledge, recognize its potential value and commercialize it through the creation of a new firm. Works in this stream (Qian and Acs 2013; Qian et al. 2013) has measured EAC in a geographical area by the presence of skilled individuals in that area and have related it to the conversion of local knowledge embodied in industrial patents into new high-tech start-ups. In this paper, we contend that the current emphasis of studies about EAC on individual skills disregards individuals' personality traits, which entrepreneurship scholars have deemed to play a crucial role in recognizing and enacting entrepreneurial opportunities (Shane and Venkataraman 2000 and Shane et al. 2003 among others). In particular, in a number of influential contributions, Florida and colleagues have related individuals' open-minded attitudes towards minorities (e.g., homosexuals and immigrants) to openness to new experiences, creativity and ability to solve complex problems (see e.g., Florida 2002a; Florida 2002b; Florida et al., 2008, among others). According to these contributions, the presence of open-minded individuals in a geographical area is positively associated to talent and concentration of high-tech industries in that area and, more generally, to higher development.

We expand on this debate and we posit that the presence of open-minded attitudes of individuals in a geographical area facilitates the leveraging of external university for the creation of innovative start-ups. As noted by Caliendo et al. (2014), open-minded individuals are prone to seek new experiences and explore novel paths. Accordingly, one can expect that they are less parochial and that tend to tap into novel and diverse sources of knowledge - including distant universities - behind the boundaries of the geographical area where they reside. Being more creative, they then have superior ability to recombine these diverse knowledge sources (Ward et al. 1997) to create radical innovations, which may form the basis for innovative start-ups. In addition, open-minded individuals are curious and extroverted (McCrae 1987) and thus are less sensitive to geographical homophily (Reuf et al. 2003). Accordingly, they likely have a more differentiated and geographically wider network of social contacts and can rely on this superior social capital for connecting with academic researchers the challenges posed by geographical distance. In turn, this familiarity with diverse and distant contacts helps open-minded-individuals understand and adopt different approaches to knowledge creation and exploitation. This greater ability to deal with diversity of perspectives, mind-frames and languages is particularly relevant for the absorption of external knowledge (see e.g., Tortoriello 2014).

According to these arguments, we conclude that a higher presence of individuals with open-minded attitudes in a geographical area is associated to a better ability to identify and enact entrepreneurial opportunities stemming from radical university knowledge created outside the area. We therefore put forth H3:

H3: Open minded-attitudes of individuals in a geographical area positively moderate the impact of external university knowledge on the creation of innovative start-ups in that area.

3. Methodology and data

3.1. Econometric specification and dependent variables

We test the aforementioned research hypotheses through various models with the following general form:

$$N\_START\_UPS_{i,j} = f(LOCAL\_UNIKNOW_{i,j}, EXT\_UNIKNOW_{i,j}, OPENNESS_{j}, CONTROLS_{i,j}). \quad (1)$$

The dependent variable $N\_START\_UPS_{i,j}$ is the number of innovative start-ups created in Italy in industry i and province j in the time period 2011-2014. Specifically, at the end of 2012, the Italian Government approved the Decree Law 179/12, which provides specific measures aimed at promoting the creation and development of a particular category of firms, which the Law labelled as innovative start-ups. The Decree Law 179/12 defines an Italian innovative start-up as an independent firm, which must comply with the following criteria. It has to: (i) be founded after December 17th 2008; (ii) have a turnover of less than 5 million; (iii) have, as a corporate mission, the development, production and commercialization of innovative high-technological products and services. Moreover, it must meet (at least) one of the following additional requirements: (a) the R&D expenses/return ratio must be greater than 15%; (b) at least 1/3 of the total workforce must possess a PhD or must have worked for at least 3 years in a research institute; (c) the firm must be the holder or the licensee of (at least) one patent. The definition of Italian innovative start-ups is consistent with the definition of YICs provided by the academic literature (e.g., Veugelers 2008). We extracted data on the population of Italian innovative start-ups from the start-up section of the Registro Imprese[3], which collects information on the geographical location, industry of operation (NACE rev. 2) and foundation year of Italian innovative start-ups established starting from 2008. The database is updated every month and, at the time of our extraction[4], the database contained information on 2,685 innovative start-ups.

When estimating equation (1), we considered only the industries for which the number of start-ups in the focal period (2011-2014) was higher than 70. In so doing, we limited the number of Italian

[3] http://startup.registroimprese.it.

[4] On October 6th, 2014.

provinces with value 0 for the industry/province pairs (see Jofre-Monseny et al. 2011 for a similar approach)[5]. This selection process leads us to consider 792 industry/province pairs[6] (8 industries * 99 provinces), accounting for 1,718 innovative start-ups operating in 8 industries. The distribution of these 1,718 start-ups by industry, foundation year and macro-regions is reported in Table 1. Furthermore, Figure 1 illustrates the geographic distribution of the number of Italian innovative start-ups created in the period 2011-2014 per million inhabitants (as in 2011), in the 99 Italian provinces considered in this study.

[Table 1 about here]

[Figure 1 about here]

To deal with the count-nature of our dependent variable and with the presence of zero observations (in 374 out of 792 industry/province pairs the number of innovative start-ups is zero), we employ a zero-inflated negative binomial estimation technique for the estimation of equation (1) (for a similar approach see, e.g., Baptista and Mendonça 2010).

3.2 Main explanatory variables

The variable $LOCAL\_UNIKNOW_{i,j}$ refers to university knowledge from universities located in the province j that constitutes the knowledge base of innovative start-up's industry i. In particular, $LOCAL\_UNIKNOW_{i,j}$ is defined as the ratio between the average number (in the period 2009-2011) of full, associate and assistant professors (i.e., the academic staff) of the universities located in

[5] See equation (1) in section 4 for the econometric specification.

[6] In this study, we use the classification at 107 provinces (valid from 2001 to 2011). In 2001, the existing provinces of Sardinia (4 provinces) were reorganized in 8 new provinces. However, in some cases statistical sources of data that provide information at the province level use the old classification. Because of these data constraints, we have therefore excluded the provinces located in Sardinia.

province j, specialized in the scientific fields that constitutes the knowledge base of the industry i (see Bonaccorsi et al. 2014b for a similar approach), and the population of the province j as in 2011.

Data on academic staff of Italian universities are extracted from the Italian Ministry of Education and Research (Ministero dell'Istruzione, dell'Università e della Ricerca, MIUR) database. Specifically, we consider the average academic staff enrolled in the period 2009-2011 in the 80 Italian research active universities. We refer to the definition reported in the EUMIDA database on European Higher Education Institutions that identifies a university as "research active" if research is considered as constitutive part of institutional activities and it is organized with a durable perspective[7]. Data on academic staff are disaggregated according to the 14 macro disciplinary areas defined by the MIUR, namely: 1) Mathematics and computer sciences; 2) Physics; 3) Chemistry; 4) Earthsciences; 5) Biology; 6) Medicine; 7) Agricultural and veterinary sciences; 8) Civil engineering and architecture; 9) Industrial and information engineering; 10) Philological-literary sciences, antiquities and arts; 11) History, philosophy, psychology and pedagogy; 12) Law; 13) Economics and statistics; 14) Political and social sciences. For each industry, we associated the university disciplinary areas (according to the MIUR classification) that constitutes the knowledge base for the focal start-up's industry, building on the findings of Schartinger et al. (2002)[8]. If, for instance, the focal start-up operates in the manufacture of machinery and equipment (C26 according to the NACE rev. 2 classification), we consider the academic specialists in the areas of mathematics and computer sciences, physics and industrial and information engineering.

Similarly, the variable $EXT\_UNIKNOW_{i,j}$ refers to university knowledge that constitutes the knowledge base of the start-up's industry i from universities located outside the focal province j.

[7] To assess these aspects, evaluation criteria were the following: (i) the existence of institutionally recognized research units; (ii) the existence of an official research mandate; (iii) the presence of regular PhD programs; (iv) the inclusion of research in the strategic planning; and (v) the regular provision of funds for research activities from public agencies as well as from private institutions. For further information see http://ec.europa.eu/research/era/docs/en/eumida-final-report.pdf.

[8] See the Appendix for Table A1 that shows the link between the YICs' industries and university disciplinary areas.

Following Bonaccorsi et al. (2014a), we assume that the effect of knowledge created by universities located outside the province j on the creation of innovative start-ups in the focal province decays with the geographical distance between the focal province j and the province k where the universities are located. In so doing, we use the following spatially weighted measure:

$$EXT\_UNIKNOW_{i,j} = \sum_{k \neq j} \frac{LOCAL\_UNIKNOW_{i,k}}{{d_{j,k}}^{\alpha}}. \tag{2}$$

where $d_{j,k}$ is the geographical distance between the focal province j and province k, $LOCAL\_UNIKNOW_{i,k}$ refers to specialized university knowledge from universities located in province k, (with $k \neq j$), and α is a distance decay parameter. We calculated distances by considering the centroid of each province (with 1 km as the unit of distance). The parameter α is set to the value that maximizes the log-likelihood of the econometric model (see Table A2 in the Appendix for the estimations obtained with different values of α). According to this procedure, the decay parameter value is 2.5.

The variable $OPENNESS_{\,j}$ is a composed index aimed at measuring the open-minded attitudes of individuals residing in province j. Using data coming from the Italian National Statistical Office (ISTAT) and grounding on the works of Florida (Florida 2008; Florida and Tinagli 2005), we build a composed index as follows:

$$OPENNESS_{\,j} = average(school\ enrollment_j;\ education_j; mixed\ families_j). \tag{3}$$

The $school\ enrollment_j$ index is defined as the ratio between the number of foreign children enrolled in primary schools and the total number of children enrolled in province j's primary schools. The $education_j$ index is the percentage of foreign population with a university degree that reside in province j. The $mixed\ families_j$ index is the percentage of families of two or more people with at least one foreign person among the components. Before taking the average value according to equation (3), we standardize the value of each sub-index (i.e., $school\ enrollment_j$, $education_j$ and $mixed\ families_j$) through the following formula:

$$Value = \frac{Value_j - min(Value)}{max(Value) - min(Value)} \tag{4}$$

To assess whether the openness of the local human capital moderates the absorption of university knowledge created outside the focal province and foster its conversion in innovative start-ups, we interact $UNIKNOW\_EXT_{i,j}$ and $OPENNESS_j$.

3.3 Controls

As to control variables ($CONTROLS_{i,j}$), we take into account the existence of agglomeration effects related to inter-industry relationships, the effect of the industrial system's variety, the presence of skilled human capital, the role of technological spillovers and the size of the provinces. To construct these variables, we combined data from several sources. In particular, we relied on the Movimprese database (e.g., number of incumbent firms operating in each province, disaggregated by industry of operation), the ISTAT database (e.g., data on the education level of the resident population, local employment in the industry of operation of innovative start-ups, population density, Input–Output Tables), and the OECD database (data on patent applications).

First, we control for the presence of agglomeration economies by considering the strengths of customer-supplier relationships (Glaeser and Kerr 2009). Following Glaeser and Kerr (2009), we calculate the relative strength of input relationships as:

$$INPUT_{i,j} = -\sum_{k=1}^{I} | Input_{i \to k} - \frac{E_{k,j}}{E_j} |; \tag{5}$$

where $Input_{i \to k}$ is the share of industry i's inputs that come from industry k, with k ϵ I (where I defines the industries according to the NACE rev. 2 classification) as reported in the Input-Output matrix (as in 2010). The variable considers the aggregate absolute deviations between the industrial inputs required by industry i, from every industry k, and the province j's actual industrial composition, in terms of share of employees (i.e., $E_{k,j}/E_j$). The variable $INPUT_{i,j}$ varies from negative two (i.e., no inputs available in the considered province) and zero (i.e., all inputs are available in the considered province in precise proportions). The relative strength of output relationships is defined as:

$$OUTPUT_{i,j} = \left[\sum_{k=1}^{I} Output_{i \to k} * \frac{E_{k,j}}{E_j}\right] * \left[\sum_{k=1}^{I} Output_{. \to k} * \frac{E_{k,j}}{E_j}\right]^{-1}; \qquad (6)$$

where $Output_{i \to k}$ is the share of industry i's outputs that go to industry k (with k ϵ I) as reported in the Input-Output matrix (as in 2010). The first bracketed term proxies the concentration of industrial sales opportunities for industry i in the province j, by multiplying the share of output of industry i that goes to industry k with the share of industry k's employment in the province j (i.e., $E_{k,j}/E_j$). By summing across industries, we measure the concentration of industrial sales opportunities for industry i in the province j. To normalize the metric, the second term in bracket is utilized, that measures the total potential industrial sales into the province. In so doing, $OUTPUT_{i,j}$ varies from zero to one, with higher values indicating greater presence of sales opportunities.

Second, several academic contribution show that the local density of incumbent firms significantly affects new firm creation in the geographical area (e.g., Bonaccorsi et al. 2013; Acs and Plummer 2014). The variable $INCUMBENT_{i,j}$ allows us to control for this aspect, by considering the number of firms registered in the industry i in the province j per inhabitants of the province. Moreover, we also consider the diversity of the local industrial system with the variable $IND\_DIVERSITY_{i,j}$. One of the most significant insights of seminal work of Jacobs (1969), recently echoed by Audretsch et al. (2010), is that the entrepreneurial activity benefits from higher degrees of diversity of the local industrial system. Following Gao (2004), we measure the industrial diversity of a province j as:

$$IND\_DIVERSITY_j = 1 - \sum_{i=1}^{I}(s_{j,i})^2 \,; \tag{7}$$

where $s_{j,i}$ is the share of firms in province j operating in the industry i, with i ϵ I, in province j. The index varies between zero and one, with higher value corresponding to higher diversity.

Third, we account for the effect of technological spillovers by including the variable $TECH_j$, which is the number of patent applications per million inhabitants in the province j as in 2010. Patent activity is often used in the literature as a proxy for knowledge generated by incumbent firms or individuals with a more immediate commercial value compared to university knowledge (Block et al. 2013; Qian et al. 2013).

Fourth, the local availability of skilled human capital ($SKILLED_j$) is measured by the percentage of adult population within the province j with either a university master or PhD degree (Qian and Acs 2013).

Lastly, we add some variables to control for the size of the province, both in terms of the size of the local labor market and of the resident population. We measure the employment in the province-industry pair ($EMPLOYMENT_{i,j}$), through the logarithm of number of employees in the industry i in the province j (Glaeser and Kerr 2009). We also control for the presence of employees in the industry i outside the province j, through the variable $EXT\_EMPLOYMENT_{i,j}$, which, mirroring the methodology used for the variable of external university knowledge, is calculated as:

$$EXT\_EMPLOYMENT_{i,j} = \sum_{k \neq j} \frac{EMPLOYMENT_{i,k}}{d_{j,k}} \tag{8}$$

where $EMPLOYMENT_{i,k}$ is the logarithm of number of employees in the industry i in the province k (with k ≠ j). As to the resident population, we control for the population density (i.e., the number of inhabitants per km^2; $DENSITY_j$) in the province as in 2011 (Bonaccorsi et al. 2014a). Finally, we also include industry and regional (NUTS2) dummies. Table 2 reports a detailed description of all the variables included in the regressions.

[Table 2 about here]

Table 3 reports the summary statistics and the correlation matrix of the variables used in the regressions.

[Table 3 about here]

4. Results

Table 4 shows the results of the econometric estimates when considering only the direct effects of the main explanatory variables included in the analysis, i.e., $LOCAL\_UNIKNOW_{i,j}$, $EXT\_UNIKNOW_{i,j}$ and $OPENNESS_j$. Results in Table 5 include also the interaction term $EXT\_UNIKNOW_{i,j} * OPENNESS_j$ [9].

Main estimates are obtained by employing a zero-inflated negative binomial technique (Column I and V), as the Vuong test (Vuong 1989; Cameron and Trivedi 2009) confirms the superior fitting performance of this model compared to the standard negative binomial regression. However, for sake of completeness we also report in Tables 4 and 5 the findings obtained when employing negative binomial (Column II and VI), poisson (Column III and VII) and tobit[10] models (Column IV and

[9] To easy the interpretation of the coefficients, in the reported estimates all the continuous variables have been standardized (mean zero and standard deviation 1).

[10] In the tobit model, the dependent variable is the logarithm of 1 + $N\_START\_UPS_{i,j}$ and the left-censoring limit is zero.

VIII)[11]. Results obtained with these additional models are in line with the zero-inflated negative binomial regressions. We thus proceed interpreting the results of Column I and V.

[Table 4 about here]

Before analysing our main explanatory variables, we briefly discuss the results concerning the control variables. As regards to the impact of agglomeration economies, we do not find evidence that the relative strength of output relationships matters for the creation of innovative start-ups at the local level. Conversely, our findings highlight the relative strength of input relationships among industries ($INPUT_{i,j}$) on the dependent variable. The coefficient of $INPUT_{i,j}$ is indeed positive and significant (p-value < 0.05). Quite interestingly, the presence in province j of incumbent firms operating in industry i does not affect the creation of innovative start-ups in industry i and province j. Indeed, the coefficient of the variable $INCUMBENT_{i,j}$ is negative, but not significant. Conversely, we find a positive and strongly significant effect of the diversity of the local industrial system on the creation of innovative start-ups in a geographical area, suggesting the importance of Jacobian externalities (Jacobs 1969) in this context. The variable $IND\_DIVERSITY_j$ has indeed a positive and significant coefficient (p-value < 0.05) in all the models. As expected, technological spillovers influence the local creation of innovative start-ups (Qian and Acs 2013), with the variable $TECH_j$ having a positive and strongly significant coefficient (p-value < 0.01). Quite surprisingly, the local availability of skilled human capital ($SKILLED_j$) is positive but not significant. Finally, the coefficients of the population density ($DENSITY_j$) and local number of employees ($EMPLOYMENT_{i,j}$) are positive and statistically significant (p-value < 0.01).

[11] The results of the likelihood ratio test reported at the bottom of Table 4 and Table 5, confirm the appropriateness of the negative binomial regression model with respect to the poisson model.

Let us now turn attention to the main explanatory variables. In line with H1, we find that the coefficient of $LOCAL\_UNIKNOW_{i,j}$ is positive and statistically significant (p value < 0.05). The average marginal effect (ME) and the average semi-elasticity (SE) of $LOCAL\_UNIKNOW_{i,j}$ on the number of innovative start-ups are 0.33 and 15%, respectively[12]. Hence, one standard-deviation increase of $LOCAL\_UNIKNOW_{i,j}$ in the focal province leads to a 15% increase in the number of innovative start-ups in the same province. Conversely, and coherently with hypothesis H2, the effect of university knowledge created outside the focal province ($EXT\_UNIKNOW_{i,j}$) is not significant. These results point out that university knowledge has an important local dimension when considering the creation of innovative start-ups. Finally, the coefficient of $OPENNESS_j$ is positive while not statistically significant.

[Table 5 about here]

Table 5 reports the results when introducing the interaction term between external university knowledge and local availability of individuals with open-minded attitudes ($EXT\_UNIKNOW_{i,j} * OPENNESS_j$). With respect to results shown in Table 4, the effects of other explanatory variables on the local creation of innovative start-ups remains substantially unchanged. The average ME and SE of $LOCAL\_UNIKNOW_{i,j}$ are 0.29 and 13%, respectively (p-value < 0.05). Again, this finding confirm hypothesis H1. The effect of $EXT\_UNIKNOW_{i,j}$ is still non-significant, while the coefficient of the interaction term $EXT\_UNIKNOW_{i,j} * OPENNESS_j$, is positive and strongly statistically significant (p-value < 0.01). Given the nonlinear specification of the zero-inflated negative binomial model, looking at the interaction term's estimated coefficients is not sufficient to assess the magnitude and the statistical significance of moderating effects. To ascertain whether $OPENNESS_j$ positively

[12] The average ME is the average increase in the number of innovative start-ups in the province/industry due to a one standard deviation increase in the variable of interest ($LOCAL\_UNIKNOW_{i,j}$), while the average SE is the average percentage increase of the dependent variable due to the same variation of $LOCAL\_UNIKNOW_{i,j}$.

moderate the effect of external university knowledge on the creation of innovative start-ups, we therefore report the average ME and SE of $EXT\_UNIKNOW_{i,j}$ as $OPENNESS_j$ varies (the solid lines in Figure 2 and Figure 3 respectively). We consider increasing values of $OPENNESS_j$, from -1.87 (the minimum value of its standardized distribution in the sample) to 1.85 (the maximum value of its standardized distribution in the sample). We estimated the 95% confidence intervals (the dashed lines) by the deltha method.

[Figure 2 about here]

As Figure 2 clearly shows, the ME of $EXT\_UNIKNOW_{i,j}$ on the creation of innovative start-ups in the focal province j increases as $OPENNESS_j$ increases. We can distinguish two regions, depending on the value of $OPENNESS_j$. First, for low values of $OPENNESS_j$ (up to the standardized value of 0.93, corresponding to the 84th percentile), one standard deviation increase of $EXT\_UNIKNOW_{i,j}$ leads to a non-significant increase in the number of innovative-start-ups in the focal province j. However, for high values of $OPENNESS_j$ (higher than 0.93 in terms of standardized value), the increase in the number of innovative start-ups in the focal province j becomes statistically significant (at least at the 5% level). Specifically, one standard deviation increase of $EXT\_UNIKNOW_{i,j}$ leads to an average 0.27 increase in the number of innovative start-ups when (the standardized value of) $OPENNESS_j$ is 1.03, while the corresponding figure is 0.61 when (the standardized value of) $OPENNESS_j$ is 1.85 (i.e., its maximum value).

[Figure 3 about here]

If we consider average SEs (Figure 3), the percentage increase in the number of innovative start-ups due to a one standard deviation increase of $EXT\_UNIKNOW_{i,j}$ switches from 12% when (the standardized value of) $OPENNESS_j$ is 1.03, to 23.5% when (the standardized value of) $OPENNESS_j$ reaches its maximum value (1.83). These results provide support to our hypothesis H3. The conversion of external university knowledge into the creation of innovative start-ups in a focal province is possible when the level of individuals' open-minded attitudes in high.

5. Conclusions

In this work, we have built on the KSTE framework (Acs et al. 2009; Ghio et al. 2014) to discuss and empirically investigate the role of university knowledge in fostering the creation of innovative start-ups at the local level. In accordance with recent contributions (e.g. Audretsch and Lehmann 2005; Acosta et al. 2011; Laursen et al. 2011; Bonaccorsi et al. 2014a), our results confirm that geographical proximity is fundamental for the exploitation of university knowledge. Specifically, university knowledge created by universities sited in a geographical area has a strong and statistically significant impact on the creation of innovative start-ups in that area. This positive effect vanishes when considering knowledge generated by distant universities. However, the local availability of open-minded individuals weakens the negative effect of geographical distance on exploitation of university knowledge for the creation of innovative start-ups.

Our work contributes to two main literature strands. First, by focusing on the creation of innovative start-ups, we add to the academic debate on YICs, which has largely focused on their growth and innovative performance (Veugelers 2008; Schneider and Veugelers 2010; Czarnitzki and Delanote 2013). Several studies have investigated the creation of new firms in high-tech and innovative industries (see e.g., the recent contribution of Fritsch and Aamoucke 2013). However, to the best of our knowledge, none of these works has take into account that a firm must meet a set of criteria well beyond its industry of operation to be labelled as innovative. By explicitly considering these criteria, we have acknowledged that YICs have a natural bent to develop radical innovations. In other words, the creation of innovative start-ups (i.e., new YICs) is a powerful mechanism through which radical knowledge developed by universities is transferred to the productive system (see Colombo et al. 2014, for a recent discussion on the role of universities in fostering radical innovations).

Second, our paper contributes to the growing literature on the KSTE (Ghio et al. 2014). Scholars in this stream have recently highlighted that EAC moderates the impact of knowledge spillovers on the creation of new firms (Qian and Acs 2013; Qian et al. 2013). Our work makes a further step in this direction in that we argue that individuals' ability to exploit university knowledge for the creation of innovative start-ups does not result only from their skills and competences, but it also relates to their personality traits. In so doing, we integrate the debate on KSTE with research in the entrepreneurship that stresses the importance of individuals' characteristics for the decision of starting a new venture (Shane 2012). In turn, this stream is part of a wider debate on the importance of individual-level characteristics and resources for understanding economic processes and organizations (e.g., Barney and Felin 2013; Devinney 2013; Felin et al. 2012).

As any other, this work has several limitations, which leave room for further inquiring. First, we move from the premise that university knowledge impacts the creation of innovative start-ups as it forms the basis for developing radical innovations. However, despite it is reasonable to assume that universities are loci where leading-edge knowledge is created, we do not directly assess the disruptive nature of the knowledge produced by a given university and used to create innovative start-ups. In addition, many radical innovations result from the re-combination of existing knowledge (Schoenmakers and Duysters 2010). Further studies should explore, for instance through case studies, how pieces of radical knowledge produced by universities are combined with less radical knowledge developed by universities or by different sources to create innovative start-ups in a geographical area. Second, we focus here on open-minded attitudes of individuals. However, the literature has shown that other personality traits (e.g., extroversion, Zhao and Seibert 2006) relate to individuals' entrepreneurial orientations and to individuals' tendency to distantly search for solutions to problems. Third, given the novelty of the observed phenomenon (Law no. 221/2012 implementing the Decree 179/2012 became effective only 19 December 2012), the limitation of available data on Italian innovative start-ups prevents us of performing time-varying analysis. Forth, the paper focuses on the Italian context and relies on data referred to a period, in which the Italian economy was still in the middle of an economic downturn. This may limit the generalizability of our results: studies repeating our analysis in other countries and in periods of economic boom will offer interesting addition to our work.

Despite the aforementioned limitations, our work is undoubtedly relevant from a policy perspective. Stimulating innovative entrepreneurship is one of the hottest issue in the current economic debate. As highlighted by the second pillar of the Entrepreneurship 2020 Action Plan promoted by the European Commission, EU Member States should support entrepreneurship by "creating the right business environment" to help young people and migrants in leveraging their creative and innovative capacities[13]. This is especially important in a country like Italy, where the economic growth is struggling to recover and the unemployment rates are particularly high[14]. In such a context, universities can offer a significant contribution as sources of radical knowledge. However, to unleash universities' potential, policymakers should design initiatives that favour the interactions between academics and perspective entrepreneurs, especially in areas where the open-minded attitudes of individuals allow them to exploit university knowledge despite the challenges posed by geographical distance.

[13] See http://ec.europa.eu/enterprise/policies/sme/entrepreneurship-2020/index_en.htm for further details.

[14] At the end of 2012, the Italian youth unemployment rate (i.e., less than 25 years old individuals) was at 37.1, while the European level was 23.5. Data available in the Eurostat website: http://epp.eurostat.ec.europa.eu/portal/page/portal/employment_unemployment_lfs/data/database.

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Tables and figures

Table 1. Distribution of innovative start-ups by industry, foundation year and macro-regions

	N. of innovative start-ups	Frequency (%)
Industry by NACE rev. 2		
C 26 - Manufacture of computer, electronics and optics products; medical equipment, measuring instruments, watches and clocks	94	5.47
C 28 - Manufacture of machinery and equipment	76	4.43
J 62 - Production of software and IT consulting activities	711	41.38
J 63 - Telecommunication and information services	200	11.64
M70 - Business management advisory and management consulting services	74	4.31
M 71 - Architecture and engineering activities	93	5.41
M 72 - Scientific research and development	383	22.3
M 74 - Other professional, scientific and technical activities	87	5.06
Total	1,718	100.00
Foundation year		
2011	218	12.69
2012	334	19.44
2013	616	35.86
2014	550	32.01
Total	1,718	100.00%
Macro-regions		
North Est	470	27.36
North West	537	31.26
Center	379	22.06
South	332	19.32
Total	1,718	100.00

Note: "South" includes also the Sicilia region.

Table 2. Variable description

Variable	Definition	Source
Dependent variable:		
$N\_START\_UPS_{i,j}$	Number of innovative start-ups created in the industry i in the province j in the period 2011-2014.	MOVIMPRESE.
Main indipendent variables:		
$LOCAL\_UNIKNOW_{i,j}$	Average academic staff (average of the period 2009-2011) of universities located in the province j specialized in scientific fields that constitute the knowledge base of the start-up's industry i per million inhabitants of the province j as in 2011.	MIUR; ISTAT.
$EXT\_UNIKNOW_{i,j}$	Average academic staff (average of the period 2009-2011) of universities located outside the focal province j specialized in scientific fields that constitute the knowledge base of the start-up's industry i per million inhabitants.	MIUR; ISTAT.
$OPENNESS_j$	Composed index that measures the local open-minded attitudes of individuals in the province j as in 2011.	ISTAT.
Controls:		
$SKILLED_j$	Share of population in the province j with a university master or PhD degree as in 2011.	ISTAT.
$DENSITY_j$	Number of inhabitants of the province j per km^2 as in 2011.	ISTAT.
$INPUT_{i,j}$	Index that measures the strength of local supplier relationships for start-ups operating in the industry i in the province j according to equation (5).	ISTAT.
$OUTPUT_{i,j}$	Index that measures the strength of local customer relationships for start-ups operating in the industry i in the province j according to equation (6).	ISTAT.
$TECH_j$	Number of patent applications per million inhabitants in the province j as in 2010.	OECD.
$EMPLOYMENT_{i,j}$	Logarithm of the number of employees in the industry i in the province j as in 2011.	ISTAT.
$IND\_DIVERSITY_j$	Industrial diversity index of the province j according to equation (7).	MOVIMPRESE.
$INCUMBENT_{i,j}$	Number of incumbent firms operating in the industry i and located in the province j per inhabitants of the province j as in 2011.	MOVIMPRESE; ISTAT.
$EXT\_EMPLOYMENT_{i,j}$	Logarithm of the number of employees in the industry i outside the province j as in 2011.	ISTAT.

Table 3. Summary statistics and correlation matrix of regression variables

	Variable	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	$N\_START\_UPS_{i,j}$	2.169	6.459	0	119	1.000												
(2)	$LOCAL\_UNIKNOW_{i,j}$	271.013	465.689	0	3053.739	0.195	1.000											
(3)	$EXT\_UNIKNOW_{i,j}$	0.112	0.129	0.002	1.143	-0.021	0.104	1.000										
(4)	$OPENNESS_{j}$	0.472	0.205	0.088	0.853	0.172	0.124	0.263	1.000									
(5)	$SKILLED_{j}$	0.136	0.026	0.096	0.215	0.274	0.606	-0.071	0.031	1.000								
(6)	$DENSITY_{j}$	258.162	336.490	38.887	2591.288	0.372	0.178	0.032	0.101	0.265	1.000							
(7)	$OUTPUT_{i,j}$	0.016	0.004	0.005	0.039	0.049	-0.066	-0.144	0.157	0.048	0.050	1.000						
(8)	$INPUT_{i,j}$	-1.557	0.207	-1.907	-0.764	0.017	-0.008	-0.170	0.150	0.114	0.085	0.156	1.000					
(9)	$TECH_{j}$	45.094	40.569	0	176.130	0.198	0.262	0.178	0.690	0.141	0.110	0.192	0.154	1.000				
(10)	$EMPLOYMENT_{i,j}$	5.662	1.725	0	10.886	0.304	0.114	-0.182	0.410	0.246	0.340	0.516	0.313	0.416	1.000			
(11)	$INCUMBENT_{i,j}$	0.524	0.381	0.113	2.849	0.154	0.116	0.117	0.360	0.112	0.156	0.503	-0.093	0.329	0.557	1.000		
(12)	$IND\_DIVERSITY_{j}$	0.904	0.031	0.808	0.941	0.171	0.154	0.221	0.662	0.110	0.231	0.150	0.138	0.577	0.394	0.308	1.000	
(13)	$EXT\_ EMPLOYMENT_{i,j}$	5.873	1.034	3.096	8.338	-0.019	-0.219	-0.147	0.413	-0.103	0.012	0.573	0.287	0.287	0.579	0.407	0.311	1.000

Table 4. Results of the econometric estimates: the effect of university knowledge on the creation of innovative start-ups

	(I)	(II)	(III)	(IV)
LOCAL_UNIKNOW$_{i,j}$	0.152**	0.169**	0.130**	0.153***
	(0.065)	(0.069)	(0.054)	(0.047)
EXT_UNIKNOW$_{i,j}$	0.097	0.077	0.066	0.055
	(0.068)	(0.068)	(0.072)	(0.046)
OPENNESS$_j$	0.172	0.238*	0.279**	0.206*
	(0.148)	(0.133)	(0.121)	(0.112)
SKILLED$_j$	0.102	0.124	0.088	0.134*
	(0.108)	(0.110)	(0.096)	(0.078)
DENSITY$_j$	0.092***	0.079***	0.076**	0.108***
	(0.026)	(0.030)	(0.033)	(0.018)
OUTPUT$_{i,j}$	0.013	0.012	0.024	0.033
	(0.078)	(0.076)	(0.069)	(0.054)
INPUT$_{i,j}$	0.290**	0.224*	0.269**	0.107
	(0.131)	(0.129)	(0.119)	(0.096)
TECH$_j$	0.183***	0.173***	0.176***	0.107*
	(0.049)	(0.065)	(0.057)	(0.064)
EMPLOYMENT$_{i,j}$	0.505***	0.576***	0.486***	0.419***
	(0.138)	(0.151)	(0.160)	(0.102)
INCUMBENT$_{i,j}$	-0.036	-0.046	0.033	-0.040
	(0.069)	(0.080)	(0.074)	(0.060)
IND_ DIVERSITY$_j$	0.192**	0.332***	0.427***	0.179**
	(0.080)	(0.122)	(0.132)	(0.087)
EXT_EMPLOYMENT$_{i,j}$	-0.503	-0.356	-0.421	-0.193
	(0.410)	(0.407)	(0.328)	(0.284)
Constant	-0.655***	-0.848***	-0.962***	-0.079
	(0.191)	(0.172)	(0.169)	(0.152)
Industry dummies	Yes	Yes	Yes	Yes
NUTS2 dummies	Yes	Yes	Yes	Yes
N. of observations	792	792	792	792
Vuong test (z)	3.10***			
LR test on overdispersion $\chi 2(1)$		84.92***		
Log likelihood	-1051.165	-1072.823	-1115.283	-711.948

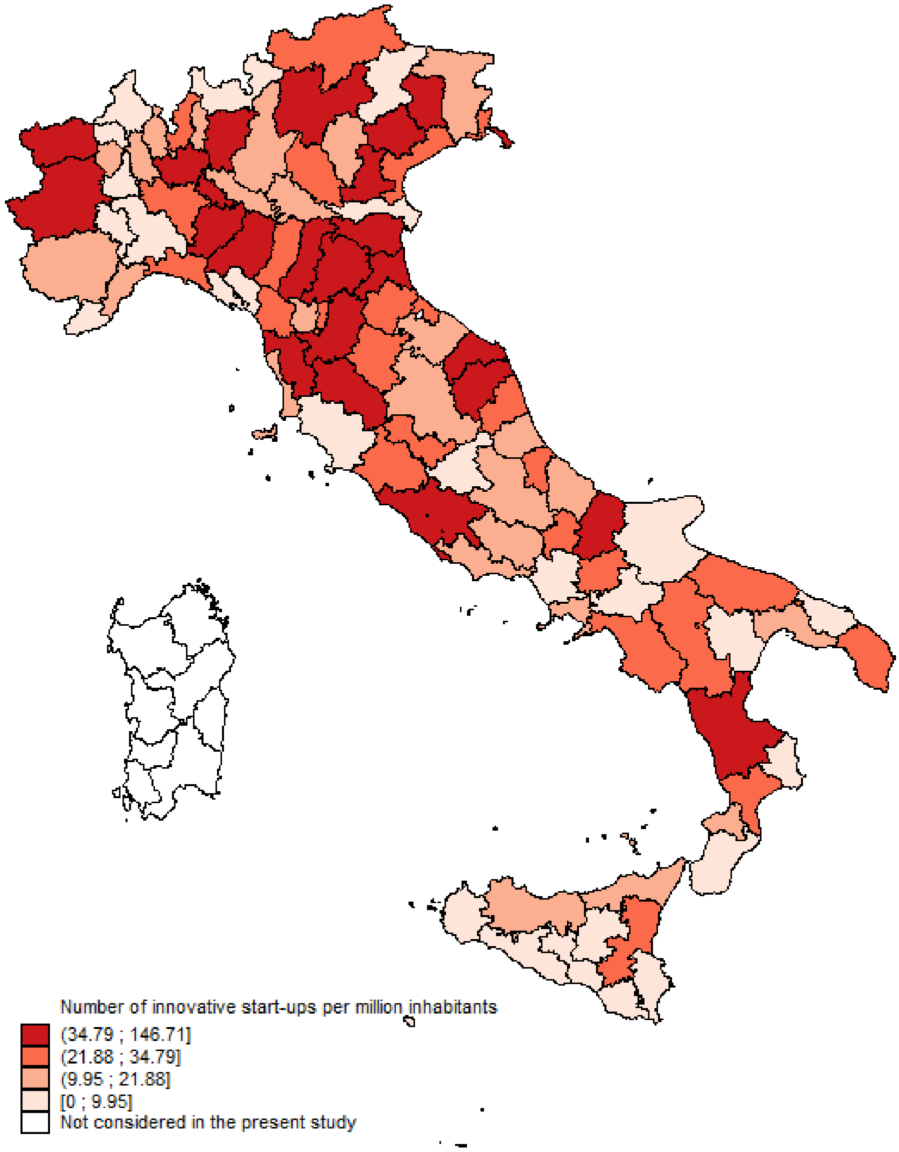
Standard errors are in brackets. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors clustered by region (NUTS2).

Table 5. Results of the econometric estimates: the moderating role of openness

	(V)	(VI)	(VII)	(VIII)
$LOCAL\_UNIKNOW_{i,j}$	0.131**	0.144**	0.112**	0.141***
	(0.064)	(0.067)	(0.052)	(0.044)
$EXT\_UNIKNOW_{i,j}$	-0.021	-0.042	-0.041	-0.008
	(0.097)	(0.098)	(0.093)	(0.056)
$OPENNESS_{j}$	0.151	0.221*	0.272**	0.190*
	(0.140)	(0.125)	(0.113)	(0.107)
$EXT\_UNIKNOW_{i,j}$ * $OPENNESS_{j}$	0.138***	0.150***	0.123**	0.095**
	(0.053)	(0.054)	(0.056)	(0.048)
$SKILLED_{j}$	0.123	0.147	0.102	0.150*
	(0.107)	(0.110)	(0.095)	(0.076)
$DENSITY_{j}$	0.084***	0.071**	0.068**	0.102***
	(0.026)	(0.030)	(0.033)	(0.018)
$OUTPUT_{i,j}$	0.007	0.002	0.021	0.027
	(0.076)	(0.074)	(0.068)	(0.052)
$INPUT_{i,j}$	0.331***	0.276**	0.303***	0.144
	(0.127)	(0.122)	(0.110)	(0.092)
$TECH_{j}$	0.183***	0.176***	0.179***	0.110*
	(0.047)	(0.063)	(0.054)	(0.063)
$EMPLOYMENT_{i,j}$	0.500***	0.569***	0.480***	0.414***
	(0.135)	(0.148)	(0.158)	(0.101)
$INCUMBENT_{i,j}$	-0.042	-0.053	0.039	-0.047
	(0.071)	(0.082)	(0.074)	(0.060)
$IND\_\ DIVERSITY_{j}$	0.187**	0.318***	0.413***	0.173**
	(0.078)	(0.120)	(0.130)	(0.086)
$EXT\_EMPLOYMENT_{i,j}$	-0.476	-0.325	-0.388	-0.165
	(0.409)	(0.406)	(0.333)	(0.288)
Constant	-0.561***	-0.741***	-0.902***	0.007
	(0.198)	(0.188)	(0.172)	(0.171)
Industry dummies	Yes	Yes	Yes	Yes
NUTS2 dummies	Yes	Yes	Yes	Yes
N. of observations	792	792	792	792
Vuong test (z)	3.10***			
LR test on overdispersion $\chi2(1)$		84.58***		
Log likelihood	-1049.593	-1070.934	-1113.225	-710.585

Standard errors are in brackets. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors clustered by region (NUTS2).

Figure 1. Geographic distribution of Italian innovative start-ups in the sample



Geographic distribution of the number of Italian innovative start-ups created in the period 2011-2014 per million inhabitants (as in 2011), in the 99 Italian provinces considered in this study.

Figure 2. Marginal effect of external university knowledge, as OPENNESS varies

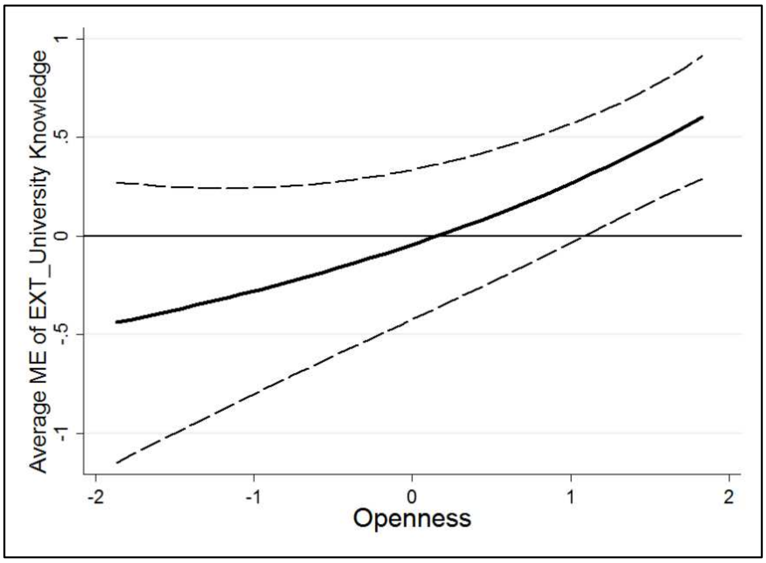
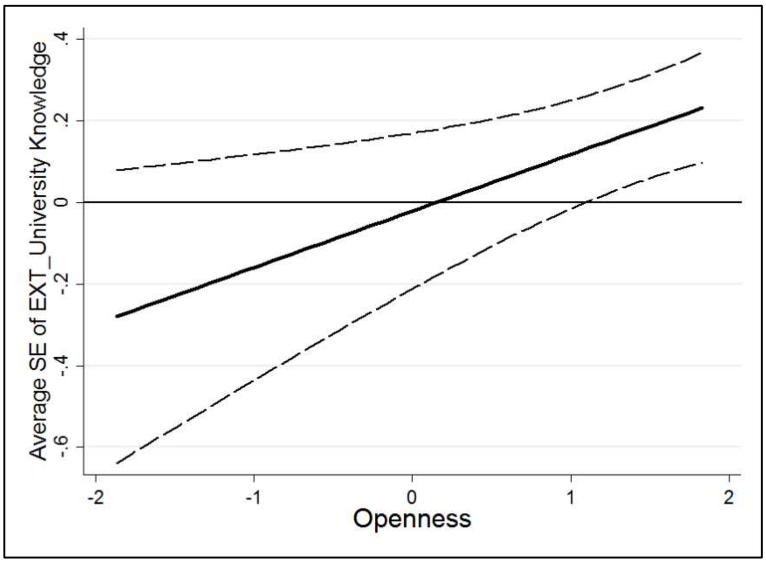


Figure 3. Semi-elasticity of external university knowledge, as OPENNESS varies



Appendix

Table A1. Link between the start-up's industry and university disciplinary areas, based on the studies of Schartinger et al. (2002)

Start-up's industry	Industry (Schartinger et al. 2002)	Scientific fields (Schartinger et al. 2002)	University disciplinary areas (MIUR)
C 26 - Manufacture of computer, electronics and optics products; medical equipment, measuring instruments, watches and clocks	Manufacturing of computers, office machinery	Electrical engineering; Physics, mechanics and astronomy.	1) Mathematics and computer sciences; 2) Physics; 9) Industrial and information engineering.
C 28 - Manufacture of machinery and equipment	Manufacturing of electronical machinery	Electrical engineering; Meteorology, climatology.	1) Mathematics and computer sciences; 2) Physics ; 9) Industrial and information engineering.
J 62 - Production of software and IT consulting activities	Software and related activities	Mathematics, informatics; Chemistry; Traffic and transport science; Other, interdisciplinary technical sciences; Economics Economic science; Spatial planning; Applied statistics, social statistics.	1) Mathematics and computer sciences; 3) Chemistry; 8) Civil engineering and architecture; 9) Industrial and information engineering; 13) Economics and statistics.
J 63 - Telecommunication and information services	Post and telecommunication services	Electrical engineering.	9) Industrial and information engineering.
M70 - Business management advisory and management consulting services	Business services	Mining, metallurgy; Economics; Engineering Technical science; Geodesy; Other, interdisciplinary technical sciences; Architecture; Spatial planning; Electrical engineering; Traffic and transport science; Construction techniques; Other, interdisciplinary social sciences; Jurisprudence; Animal production; Political science; Mathematics, informatics; Physics, mechanics and astronomy; Sociology; Hydrology, hydrography; Biology, botanics and zoology; Psychology; Educational science.	1) Mathematics and computer sciences; 2) Physics; 5) Biology; 8) Civil engineering and architecture; 9) Industrial and information engineering; 11) History, philosophy, psychology and pedagogy; 12) Law; 13) Economics and statistics; 14) Political and social sciences.
M 71 - Architecture and engineering activities	NA	NA	4) Earthsciences; 5) Biology; 6) Medicine; 8) Civil engineering and architecture; 13) Economics and statistics.
M 72 - Scientific research and development; M 74 - Other professional, scientific and technical activities	Research and development	Mining, metallurgy; Engineering; Construction techniques; Architecture; Electrical engineering; Economics; Geodesy; Traffic and transport science; Other, interdisciplinary technical sciences; Spatial planning; Other, interdisciplinary social sciences; Political science; Jurisprudence; Animal production; Political science; Mathematics, informatics; Physics, mechanics and astronomy; Sociology; Hydrology, hydrography; Biology, botanics and zoology; Psychology; Educational science.	1) Mathematics and computer sciences; 2) Physics; 4) Earthsciences; 5) Biology; 7) Agricultural and veterinary sciences; 8) Civil engineering and architecture; 9) Industrial and information engineering; 11) History, philosophy, psychology and pedagogy; 12) Law; 13) Economics and statistics; 14) Political and social sciences.

NA: Not Available, the industry is not considered in the study

Table A2. Estimation of the decay parameter

	(A.I)	(A.II)	(A.III)	(A.IV)	(A.V)
LOCAL_UNIKNOW$_{i,j}$	0.150**	0.144**	0.137**	0.131**	0.127**
	(0.064)	(0.065)	(0.065)	(0.064)	(0.063)
EXT_UNIKNOW$_{i,j}$	0.208	0.110	0.037	-0.021	-0.062
	(0.180)	(0.131)	(0.106)	(0.097)	(0.102)
OPENNESS$_j$	0.169	0.159	0.151	0.151	0.158
	(0.154)	(0.147)	(0.141)	(0.140)	(0.142)
*EXT_UNIKNOW$_{i,j}$ * OPENNESS$_j$*	-0.009	0.042	0.096**	0.138***	0.159**
	(0.045)	(0.043)	(0.045)	(0.053)	(0.070)
SKILLED$_j$	0.101	0.106	0.115	0.123	0.126
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
DENSITY$_j$	0.097***	0.094***	0.089***	0.084***	0.083***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
OUTPUT$_{i,j}$	0.016	0.009	0.006	0.007	0.010
	(0.080)	(0.079)	(0.077)	(0.076)	(0.076)
INPUT$_{i,j}$	0.271**	0.294**	0.317**	0.331***	0.332**
	(0.138)	(0.132)	(0.128)	(0.127)	(0.129)
TECH$_j$	0.183***	0.182***	0.182***	0.183***	0.185***
	(0.048)	(0.048)	(0.048)	(0.047)	(0.046)
EMPLOYMENT$_{i,j}$	0.507***	0.512***	0.510***	0.500***	0.491***
	(0.141)	(0.139)	(0.137)	(0.135)	(0.135)
INCUMBENT$_{i,j}$	-0.028	-0.033	-0.038	-0.042	-0.042
	(0.069)	(0.069)	(0.070)	(0.071)	(0.071)
IND_ DIVERSITY$_j$	0.205**	0.193**	0.186**	0.187**	0.192**
	(0.080)	(0.078)	(0.077)	(0.078)	(0.080)
EXT_EMPLOYMENT$_{i,j}$	-0.496	-0.475	-0.471	-0.476	-0.480
	(0.414)	(0.410)	(0.408)	(0.409)	(0.411)
Constant	-0.880***	-0.732***	-0.629***	-0.561***	-0.532***
	(0.323)	(0.258)	(0.219)	(0.198)	(0.188)
Industry dummies	Yes	Yes	Yes	Yes	Yes
NUTS2 dummies	Yes	Yes	Yes	Yes	Yes
Num. observations	792	792	792	792	792
Vuong test (z)	3.07**	3.10***	3.11***	3.10***	3.08***
Log Likelihood	-1051.365	-1050.877	-1050.064	-1049.593	-1049.765

Standard errors are in brackets. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors clustered by region (NUTS2). Reported coefficients are obtained with zero inflated negative binomial regression as the Vuong test confirms its superior fitting to the classic negative binomial regression. Column A.I, A.II, A.III, A.IV, A.V reports the coefficients as well as the Log likelihood of the models estimated with the decay parameter α set at 1, 1.5, 2, 2.5, 3 respectively. The model which maximize the Log Likelihood is A.IV, α = 2.5.