Do local diversity and availability of human capital boost the exploitation of university knowledge spillovers by prospective entrepreneurs? The case of the creation of innovative start-ups in Italy

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Abstract

In this paper, we investigate whether and how the characteristics of a territory impact in the local creation of innovative start-ups, in Italy. We argue that local knowledge spillovers from universities foster the creation of innovative start-ups. However, we claim that specific characteristics of a territory boost the commercial exploitation of knowledge spillovers by prospective entrepreneurs. More specifically, we investigate whether the *local availability of skilled human capital* as well as its *diversity* moderate the exploitation of university knowledge spillovers in the creation of innovative start-ups. We estimate a series of linear regressions on a sample of 792 province-industry pairs that are formed by crossing 99 Italian Provinces with 8 industries. Our results show that the local presence of knowledge spillovers from universities increases the number of innovative start-ups. Moreover, we find that the local availability of skilled human capital seems to be complementary to the university knowledge spillovers in fostering the creation of innovative start-ups, while local diversity reduces the positive impact of university knowledge spillovers.

1. Introduction

Stimulating innovation and entrepreneurship is one of the hottest issue in the current economic debate. This is especially true in a country like Italy, where the economic growth is struggling to recover and the unemployment rates are particularly high. In an effort to help innovative entrepreneurship and stimulate growth, 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 that the Law labelled *innovative start-ups*. Namely, the Decree Law 179/12 defines an innovative Italian start-up as an independent firm, which must have the following characteristics. It has to: (i) be founded after the 17th of December 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 complies with (at least) one of the following additional requirements: (a) have the R&D expenses/return ratio greater than 30%, (b) at least 1/3 of the total workforce must possess a PhD or a university degree and having worked for at least 3 years in a research institute, (c) be the owner or licensee of (at least) one patent.

In sum, innovative start-ups are likely to have a natural bent to innovation and to base their competitive advantage on the development of leading-edge knowledge. Considering the peculiarities of innovative start-ups, it is reasonable to expect that, in line with the Knowledge Spillover Theory of Entrepreneurship (hereafter KSTE: Audretsch, 1995; see Ghio et al., 2014 for a recent review) framework, the creation of these firms is highly responsive to knowledge spillovers from universities.

Building on recent developments of the literature on KSTE (Qian and Acs, 2013), in this paper we study how knowledge spillovers generated by the presence of university in a geographical area and the characteristics of human capital available in that area *interact* to explain variations in the creation of *innovative start-ups* across Italian provinces (NUTS3 level). Specifically, we consider two main characteristics of the local human capital that allegedly influence the *recognition* and the *enacting* of the entrepreneurial opportunities originating from university knowledge spillovers: *the local availability of skilled human capital and its diversity*. Most previous papers on the role of university knowledge spillovers in fostering local entrepreneurship (e.g. Audretsch and Lehmann, 2005; Acosta et al., 2011) have not considered how these local characteristics moderate the impact of university knowledge spillovers on the new firm creation. An important contribution of this paper is therefore to analyze the extent to which these local characteristics facilitate the commercial exploitation of university knowledge spillovers.

To address these research questions, we run a series of linear regressions where the dependent variable is the logarithm of the number of innovative start-ups in the industry/province. As to the explanatory variables, we refer to the knowledge produced by the universities in the province, the local availability of skilled human capital (measured by the percentage of people with at a university degree), and its cultural diversity. We control for agglomeration effects related to labor market pooling, customer–supplier relationships and technological spillovers, and for the development of the local financial system and unemployment rate. Data come from the combination of different information sources. Data on: i) innovative start-ups are extracted from the Movimprese database[1]; ii) Italian universities are extracted from the MIUR statistical office; iii) local employment, nationality of population and customer-supplier relationship are extracted from the Istat database, iv) patent applications and unemployment rate are extracted from the OECD database.

The paper is organized as follows. The next section provides the theoretical background and hypotheses development. Section 3 describes data sources, the econometric specification and the variables used in the estimations. Section 4 presents the results of the econometric analysis. Section 5 concludes.

2. Theoretical background and hypotheses development

A substantial amount of research has focused on the influence that knowledge spillovers from universities exerts on the innovation of firms located in neighbouring geographical areas (e.g., Jaffe 1989; Anselin et al., 1997; 2000; Belenzon and Schankerman, 2013). More recently, scholars have focused attention on the impact of universities on the creation of new firms at the local level, using the theoretical lens of the Knowledge Spillover Theory of Entrepreneurship (hereafter KSTE: Audretsch, 1995). KSTE emphasizes the role of knowledge spillovers in stimulating entrepreneurship. In the KSTE framework, the creation of a new venture is viewed as a response to opportunities stemming from knowledge generated and not commercially exploited by incumbent firms or public research institutions (Acs et al., 2013). In particular, several articles within the KSTE theoretical framework have provided evidence of a positive relationship between knowledge generated by universities and new firm creation at the local level (see among the others, Audretsch and Lehmann, 2005; Bonaccorsi et al., 2014; Acosta et al., 2011).

According to KSTE and considering the peculiarities of the innovative start-ups as classified by the Italian regulation, we expect that the theoretical framework of the KSTE holds also for such a specific type of start-ups. Therefore, we posit hypothesis H1.

[1] For further information see http://startup.registroimprese.it

H1. *University knowledge spillovers positively impact on the creation of innovative start-ups.*

However, university knowledge spillovers may be not enough to foster entrepreneurship at the local level. We argue that certain characteristics of a territory can magnify the effect of these spillovers on the creation of innovative start-ups, by favouring their exploitation by prospective entrepreneurs. In this view, Qian and Acs (2013) have argued that skilled human capital is a major determinant of the *entrepreneurial absorptive capacity,* which allows prospective entrepreneurs to value new knowledge and commercialize it by creating new firms. Entrepreneurial absorptive capacity is likely to be crucial for the creation of an innovative start-up. First, knowledge generated by universities is just partially formed and not developed for commercialization (Stephan, 2012). Moreover, it must be recombined in novel ways in order to create innovative products and services with a high-technology content. Because of their natural bent to innovation and the knowledge-based nature of their production processes, it is reasonable to expect that human capital is one of the most important resource for an innovative start-ups. Hence, it is reasonable to expect that new knowledge from universities is needed *together* with the human capital of the workers, which enables the start-up to better appropriate of its value. It follows that:

H2. *The local availability of human capital positively moderates the relationship between knowledge spillovers from universities and the creation of innovative start-ups*.

As to local diversity, the seminal work by Jacobs (1969) suggests that local diversity foster entrepreneurship by facilitating knowledge spillovers. In a recent work, Audretsch et al. (2010) distinguish between sectoral and individual diversity of a region. Interestingly enough, the authors find empirical support to the idea that it is the individual diversity, as measured by a Theil index reflecting both the share and the variety of the nationalities of the population in the considered area, which mostly affects the creation of new firms in high-tech industries in Germany. Their results suggest that diversity of people is more conducive to entrepreneurship than the diversity across firms. Indeed, diverse individuals are able to evaluate new knowledge differently, thus responding to different entrepreneurial opportunities in different ways. A similar theoretical argument is adopted by Cheng and Li (2012), who provide evidence to the fact that the cultural as well as racial regional diversity affect the local creation of new firms. Moreover, a recent stream of literature has been focused on the relationship between cultural diversity and firms' innovation performances, which are focal for type of firms in which we are focusing. A recent article by Niebuhr (2010), provides evidence to the fact that workers' individual diversity positively affect the innovation output in German regions. This is related to the fact that cultural diversity may lead to innovation since it involves variety in abilities and knowledge (Alesina and La Ferrara, 2005). Building on these recent articles, we contend that provinces with higher degree of local cultural diversity are endowed with a wider availability of people with different mindsets and cultural backgrounds that led to higher entrepreneurial rates.

H3. *Local diversity positively influences the creation of innovative start-ups.*

Moreover, since our focal firms operate in knowledge-intensive sectors, knowledge should be the principal asset of these innovative start-ups. Consequently, local areas characterized by a greater availability of different mindsets should be more open to different ways through which the knowledge available locally can be exploited, thus enjoying higher rate of innovative start-ups creation. In other words, we expect that:

H4. *Local diversity positively moderates the relationship between knowledge spillovers from universities and the creation of innovative start-ups.*

3. Method and Data sources

3.1 Econometric specification and variables description

To address the research questions, we run a series of linear regressions where the dependent variable is the logarithm of the number of innovative start-ups by industry *i* and province *j*. We estimate OLS models of the type:

$$\text{Log(START-UPS)}_{i,j} = f(UNIKNOW_{i,j}, SKILLED_j, DIVERSITY_j, CONTROLS_{i,j}). \quad (1)$$

The variable $UNIKNOW_{i,j}$ refers to knowledge spillovers from universities located in the province *j* that are relevant for the to the start-up's industry *i*. It is measured by the percentage of the academic staff of the universities located in province *j*, specialized in the scientific fields that constitutes the knowledge base of the industry *i* (see Bonaccorsi et al., 2014 for a similar approach). Specifically, for each start-up's industry we associated the university disciplinary areas (according to the classification presented in section 3.2) that constitutes the knowledge base for that industry, building on the findings of Cohen et al. (2002) and Schartinger et al. (2002)[2].

[2] See the Appendix for a Table that show the link between the start-up's industry and university disciplinary areas.

Local availability of skilled human capital ($SKILLED_j$) is measured by the percentage of adult population within the province *j* with a university degree or higher (Qian and Acs 2013). To assess the degree of the local diversity of a province, building on the articles by Audretsch et al. (2010) and Cheng and Li (2012), we consider a Theil index. For a given province *j*, the Theil index for local diversity is defined as follows:

$$DIVERSITY_j = -\sum_{m=1}^{Mj} s_{j,m} * \ln s_{j,m} \ ; \qquad (2)$$

where $s_{j,m}$ is the share of the population in province *j* belonging to nationality *m*, and M_j is the number of different nationalities in province *j*. As a consequence, the Theil index has maximum value $\ln(M_j)$, in a province where the shares of all population groups are identical ($s_{j,m} = 1/M_j$). Conversely, if the population of a province is composed by just one ethnic group, the index takes the value $\ln(1) = 0$.

Furthermore, in order to assess whether the local availability of skilled human capital and its diversity moderate the allegedly positive impact of university knowledge spillovers on start-up creation, we interact $UNIKNOW_{i,j}$ with $SKILLED_j$ and $DIVERSITY_j$[3].

As to control variables ($CONTROLS_{i,j}$), we take into account the existence of agglomeration effects related to labor market pooling, customer–supplier relationships and technological spillovers (Glaeser and Kerr, 2009). Labor market pooling refers to the advantages that firms and employees obtain from locating in a thick labor market. Following Glaeser and Kerr (2009), we calculate the labor market pooling variable ($LABOR_{i,j}$) as the availability of province *j*'s labor market for a new firm in the industry *i*, using the following equation:

$$LABOR_{i,j} = -\sum_{o=1,2,\ldots,O} |L_{i,o} - \left(\sum_{k=1,\ldots,I} \frac{E_{k,c}}{E_c} L_{k,o}\right)|; \qquad (3)$$

where *O* indicates the occupations. $L_{i,o}$ captures the percentage of industry *i*'s employment in occupation *o* and $\frac{E_{k,c}}{E_c}$ indicates the proportion of workers in the province *j*, employed in industry *k*. As to customer-supplier relationships, the relative strength of Input relationships is defined as:

$$INPUT_{i,j} = -\sum_{k=1,\ldots,I} |\, Input_{i\rightarrow k} - \frac{E_{k,c}}{E_c} |; \qquad (4)$$

[3] To facilitate the interpretation of estimated coefficients, before running OLS regression we standardized (0 mean, 1 standard deviation) the variables $UNIKNOW_{i,j}$, $SKILLED_j$ and $DIVERSITY_j$.

where $Input_{i \to k}$is the share of industry *i*'s inputs that come from industry *k*. The variable considers the aggregate absolute deviations between the industrial inputs required by industry *i*, from every industry sector, and the province *j*'s actual industrial composition, in terms of share of employees for every industry-sectors. The measure 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:

$$OUTPUT_{ij} = \left[\sum_{k=1,\dots,I} Output_{i \to k} * \frac{E_{k,c}}{E_c}\right] * \left[\sum_{k=1,\dots,I} Output_{. \to k} * \frac{E_{k,c}}{E_c}\right]^{-1}; \qquad (5)$$

where $Output_{i \to k}$ is the share of industry i 's outputs that go to industry *k*.

The first bracketed term proxies the concentration of industrial sales opportunities for industry *i* in the considered province *j*, by multiplying the share of sales of industry *i* that goes to industry *k* with the share of industry k's employment in the province *j*. By summing across industries, we measure the concentration of industrial sales opportunities for industry i in the considered province *j*. To normalize the metric, the second term in bracket is utilized, that measures the total potential industrial sales into the considered province. In so doing, $OUTPUT_{ij}$ varies from zero to one, with higher values indicating greater presence of sales opportunities.

Finally, we account for technological spillovers by including the variable TECH_j, which is 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 market compared to the university knowledge (Block et al., 2010; Qian and Acs, 2013).

We further control for employment in the province-industry by including the number of employees in the industry *i* in the province *j* ($\mathrm{Log(EMPLOYMENT)}_{i,j}$), local financial development (FIN_j), using the number of bank branches per 100,000 inhabitants in the province *j*, and the unemployment rate in the province *j* ($\mathrm{UNEMPLOYMENT}_j$). Finally, we also include industry and regional (NUTS2) dummies. Table 1 reports a detailed description of all the variables included in the regression.

[Table 1 about here]

Table 2 reports the summary statistics and Table 3 the correlation matrix.

[Table 2 about here]

[Table 3 about here]

3.2 Data sources

To build our variables of interest we combined data coming from different information sources. Data on innovative start-ups are extracted from the Movimprese database and, specifically, from the *start-up* section of the *Registro Imprese*[4], which collects information on the geographical location, industry of operation (NACE rev. 2) and foundation year on 2,053 start-ups[5] established starting from 2008. We considered only the industries for which number of start-ups in the focal period (2011-2014) was higher than 60. In so doing, we limited the number of provinces with value 0 for our dependent variable (see Jofre-Monseny et al., 2011 for a similar approach). This selection process led us to include 8 industries, namely: manufacture of computer, electronics and optics products (79 start-ups); manufacture of machinery and equipment (62 start-ups); production of software and IT consulting activities (578 start-ups); telecommunication services (156 start-ups); business management advisory and management consulting services (63 start-ups); architecture and engineering activities (76 start-ups); scientific research and development (316 start-ups); other professional, scientific and technical activities (65 start-ups)[6]. As regards to the Italian provinces, we started from the current list of 110 Italian provinces, then we dropped the 8 provinces from Sardegna region due to the recent reclassification. For the same reason, we aggregated the province of Monza-Brianza in the Province of Milano, the province of Barletta Andria Trani in the province of Foggia and the province of Fermo in the province of Ancona. Our final dataset therefore consists of 792 observations, consisting in (99*8) province-industry pairs.

We extracted data on Italian universities from the Italian Ministry of Education and Research *(Ministero dell'Istruzione, dell'Università e della Ricerca,* MIUR*)* database. Specifically, to build our measure of university knowledge spillovers, we extracted data on the academic staff (i.e., full, associate and assistant professors) enrolled in the period 2004-2008 in the 80 Italian research active universities. We refer to the definition reported in the EUMIDA database on European Higher Education Institutions[7] 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. To assess

[4] For further information see http://startup.registroimprese.it.

[5] On May 19th, 2014.

[6] Corresponding to the NACE rev. 2 codes C26, C28, J62, J63, M70, M71, M72, M74 respectively.

[7] For further information see http://ec.europa.eu/research/era/docs/en/eumida-final-report.pdf

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.

Data are disaggregated according to the 14 macro disciplinary areas defined by the MIUR: 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.

Furthermore, we extracted information related to local human capital characteristics in each Italian province (i.e. population with university degree and information of nationality) from the Italian national statistical office (ISTAT). The ISTAT database also provided data for the construction of control variables, i.e. data on local employment in the start-up's industry of operation, unemployment rates and Input–Output Tables to characterize customer–supplier relations. Finally, information on patent application is extracted from the OECD database.

4. Results

Table 4 reports the results of a series of linear regressions.

[Table 4 about here]

First, in column (I) we report the empirical evidence on the relationship between university knowledge spillovers and the local creation of innovative start-up in Italy, when controlling for agglomeration mechanisms and other local characteristics. In line with H1 and with previous articles having investigated the extent to which activities within universities positively affect the local creation of new firms (Audretsch and Lehmann 2005, Bonaccorsi et al. 2014, Acosta 2011), we find that the coefficient of $UNIKNOW_{i,j}$ is positive and statistically significant at the 1% level. Second, column (II) reports our findings when we add the variable for local availability of skilled human capital ($SKILLED_j$). Results suggest a strong positive effect of the local presence of skilled people in explaining the local creation of innovative start-up. The coefficient of skilled is indeed positive and statistically significant at the 1%. This result appears to be consistent with the works by Piva et al., (2011) and by Qian and Acs (2013) having provided evidence to the important role of the local human capital in terms of enhancement of entrepreneurial absorptive capacity (Qian and Acs, 2013). Furthermore, the effect of the variable measuring the university knowledge spillovers is still positive and significant.

Column (III) shows the results when we consider the interaction effect between university knowledge spillovers and local availability of human capital. The interaction term appears to be not statistically significant. However, to further shed light on the moderating role of the local availability of skilled human capital on the positive effect of university knowledge spillovers, in Table 5 we report the marginal effect of $UNIKNOW_{i,j}$ for different values of $SKILLED_j$. Table 5 cleary shows that the marginal effect of $UNIKNOW_{i,j}$ on the local creation of innovative start-ups increases as the availability of skilled human capital increases, thus suggesting the existence of a complementarity effect between these two variables, in line with H2.

[Table 5 about here]

In Column (IV) we introduce local cultural diversity. Results clearly show that local cultural diversity positively affects the local creation of innovative start-ups within its boundaries. The coefficient of $DIVERSITY_j$ is indeed positive and statistically significant at the 10%. We thus find support for H3. Again, the variable measuring the university knowledge spillovers appears to be positive and significant in explaining the local creation of innovative start-ups. Finally, in column (V) we add the interaction term between university knowledge spillovers and local diversity. While the university knowledge spillovers are still positive and significant, the interaction term appears to be negative, even if not statistically significant. We report the marginal effect of $UNIKNOW_{i,j}$ for increasing values of $DIVERSITY_j$ in Table 6.

[Table 6 about here]

Quite surprisingly, results show that the marginal effect of university knowledge spillovers appears to be positive and significant for different values of $DIVERSITY_j$. However, we observe a decreasing trend as the local diversity increases, thus suggesting a substitution effect of these two variables. This latter result therefore does not confirm H4.

As control variables, we find evidence that the local availability of a suitable labor market for the start-up's industry ($LABOR_{i,j}$) has a positive and significant effect on the local creation of innovative start-ups in most estimates. Quite interestingly, the effect of $LABOR_{i,j}$ becomes not significant when we add $SKILLED_j$ and its interaction term with $UNIKNOW_{i,j}$ (Column III). This latter result suggests that the labor market that is relevant for the creation of innovative start-ups is the skilled labor market. Moreover, we find strong evidence (persistent all our specifications) of a positive effect of the local number of employees. Conversely, we find weak evidence to the fact that relative strength of input-output relationships (e.g., customer-supplier relationships) impact the local creation of innovative start-ups. A possible interpretation for these results is that innovative start-ups in our sample operates in industries that are not dependent on the local availability of physical inputs or output (i.e., the R&D sectors).[8] As expected, we find a strong and positive effect for the local patent activity ($TECH_j$) in explaining the local creation of innovative start-ups. Interestingly, this effect appear to be robust, since it persists in all our specifications. Moreover, we find no evidence on the role of the local financial system. This latter result is in line with the entrepreneurial finance literature, which has assessed that the bank capital is not the best way of financing innovative activities, while equity financing is more appropriate for start-ups operating in R&D intensive industries and thus characterized by higher information asymmetries and lack of collateral (Berger and Udell, 1998; Gompers and Lerner, 2001; Ueda, 2004), Finally, we find no evidence for the role of the local unemployment rate, suggesting that these innovative start-up creation is not related to necessity entrepreneurship. This finding is not surprisingly in light of the importance of skilled human capital for the creation of these firms.

5. Conclusion

Innovative start-ups - by introducing new products, processes and organizational innovations - are fundamental for the static and dynamic efficiency of the economic system (Audretsch, 1995). For these reasons, a better understanding on the extent to which local characteristics moderate the conversion of university knowledge spillovers into the creation of new innovative start-ups can have relevant policy implications.

According to previous evidence on KSTE, our results show that knowledge spillovers from university positively influence the local creation of innovative start-ups. Furthermore, local availability of skilled human capital seems to be complementary to university knowledge spillovers, while local diversity reduces the positive impact of university knowledge spillovers. These results therefore suggest the need for policies aimed at attracting skilled people in order to favor the commercial exploitation of university knowledge spillovers via entrepreneurship.

The paper contributes to the growing literature on the KSTE (Ghio et al. 2014) and, specifically, to the ongoing debate on the role of university in fostering local entrepreneurship (e.g. Audretsch and Lehmann, 2005; Bonaccorsi et al., 2014; Acosta et al., 2011). Previous works in the KSTE stream have disregarded how the local availability of skilled human capital and its diversity

[8] Extant literature having assessed the importance of input-output relationships is mainly focused on traditional manufacturing sectors (e.g. Glaeser and Kerr, 2009).

moderate the impact of university knowledge spillovers on new firm creation. The research presented in this paper may be therefore viewed as a further step towards a better understanding of the mechanisms that drive the conversion of new knowledge produced in university R&D laboratories into commercialized knowledge.

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Table and Figures

Table 1 – Variable description

Variable	Definition
Dependent variable:	
Log(START_UPS)$_{i,j}$	Logarithm of the number of innovative start-ups in the industry *i* in the province *j* in the period 2011-2014.
Main indipendent variables:	
UNIKNOW$_{i,j}$	Percentage of academic staff in the universities of the in the province *j* specialized in scientific fields that constitute the knowledge base of the industry *i* (period 2004-2008).
SKILLED$_j$	Share of population in the province *j* with university degree or higher as in 2001.
DIVERSITY$_j$	Theil index that measures the local cultural diversity in the province *j* as in 2010.
Controls:	
FIN$_j$	Number of bank branches per 100,000 inhabitants in the province *j* as in 2010.
TECH$_j$	Number of patent applications per million inhabitants in the province *j* as in 2010.
UNEMPLOYMENT$_{i,j}$	Unemployment rate in the province *j* as in 2010.
OUTPUT$_{i,j}$	Index that measures the strength of relationships with potential buyers of products of start-ups operating in the industry *i* in the province *j*.
INPUT$_{i,j}$	Index that measures the strength of the relationships with potential suppliers of products required by start-ups operating in the industry *i* in the province *j*.
LABOR$_{i,j}$	Index that measures the local availability of suitable employees to the industry *i* in the province *j*.
Log(EMPLOYMENT)$_{i,j}$	Logarithm of the number of employees in the industry *i* in the province *j* as in 2011.

Table 2 – Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log(START_UPS)$_{i,j}$	792	0.50	0.74	0	4.54
UNIKNOW$_{i,j}$	792	0.11	0.15	0	0.90
SKILLED$_j$	792	11.74	2.06	7.99	18.93
DIVERSITY$_j$	792	0.59	0.24	0.13	1.04
FIN$_j$	792	60.80	22.30	21	142
TECH$_j$	792	38.61	86.72	0	752.79
UNEMPLOYMENT$_{i,j}$	792	8.25	3.71	2.71	19.21
OUTPUT$_{i,j}$	792	0.01	0.01	0	0.11
INPUT$_{i,j}$	792	-1.30	0.12	-1.54	-0.72
LABOR$_{i,j}$	792	-0.80	0.33	-1.21	-0.04
Log(EMPLOYMENT)$_{i,j}$	792	5.66	1.72	0	10.88

Table 3 – Correlation matrix

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Log(START_UPS)$_{i,j}$	1.00										
(2)	UNIKNOW$_{i,j}$	0.27	1.00									
(3)	SKILLED$_j$	0.31	0.32	1.00								
(4)	DIVERSITY$_j$	0.20	-0.04	-0.04	1.00							
(5)	FIN$_j$	0.16	-0.05	-0.12	0.78	1.00						
(6)	TECH$_j$	0.44	0.23	0.30	0.38	0.37	1.00					
(7)	UNEMPLOYMENT$_{i,j}$	-0.10	-0.00	0.07	-0.75	-0.71	-0.22	1.00				
(8)	OUTPUT$_{i,j}$	-0.01	-0.10	-0.01	0.17	0.15	0.11	-0.18	1.00			
(9)	INPUT$_{i,j}$	-0.13	0.10	0.08	0.22	0.18	0.24	-0.19	0.50	1.00		
(10)	LABOR$_{i,j}$	-0.24	-0.07	0.09	0.03	0.00	0.07	-0.00	0.55	0.52	1.00	
(11)	Log(EMPLOYMENT)$_{i,j}$	0.31	0.17	0.22	0.37	0.30	0.49	-0.28	0.56	0.40	0.34	1.00

Table 4 – Results from econometric estimates

	(I)	**(II)**	**(III)**	**(IV)**	**(V)**
FIN_j	-0.0016	-0.0014	-0.0015	-0.0027	-0.0032
	(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0020)
$TECH_j$	0.0021***	0.0018***	0.0017***	0.0021***	0.0022***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$INPUT_{i,j}$	0.6033*	0.5493*	0.6012*	0.5693*	0.5799*
	(0.3249)	(0.3217)	(0.3231)	(0.3249)	(0.3251)
$OUTPUT_{i,j}$	-5.2931*	-4.2014	-4.5471	-4.7970*	-5.0066*
	(2.8072)	(2.7893)	(2.7951)	(2.8148)	(2.8228)
$LABOR_{i,j}$	1.0602***	0.5366*	0.4603	1.0375***	1.0849***
	(0.2972)	(0.3195)	(0.3228)	(0.2970)	(0.3008)
$Log(EMPLOYMENT)_{i,j}$	0.1283***	0.1139***	0.1168***	0.1201***	0.1193***
	(0.0208)	(0.0208)	(0.0209)	(0.0212)	(0.0212)
$UNEMPLOYMENT_{i,j}$	0.01277	0.0176	0.0178	0.0153	0.0139
	(0.0111)	(0.0110)	(0.0110)	(0.0111)	(0.0112)
$UNIKNOW_{i,j}$	0.0831***	0.0578**	0.0620***	0.0910***	0.0860***
	(0.0230)	(0.0236)	(0.0237)	(0.0234)	(0.0239)
$SKILLED_j$		0.1243***	0.1124***		
		(0.0297)	(0.0306)		
$UNIKNOW_{i,j}$ * $SKILLED_j$			0.0379		
			(0.0239)		
$DIVERSITY_j$				0.0897*	0.0838*
				(0.0475)	(0.0479)
$UNIKNOW_{i,j}$ * $DIVERSITY_j$					-0.0231
					(0.0233)
Constant	0.4953	0.5880	0.5436	0.8480	1.3061***
	(0.5010)	(0.4978)	(0.4925)	(0.4833)	(0.4997)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes
R-squared	0.5376	0.5481	0.5496	0.5398	0.5404
Observations	792	792	792	792	792

Legend: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. Standard errors in round brackets.

Table 5 - Marginal effect of university knowledge spillovers for different percentiles of the local availability of skilled human capital

	Marginal effect of $UNIKNOW_{i,j}$
$SKILLED_j$ at the:	
10^{th} percentile	0.0131
	(0.0368)
20^{th} percentile	0.0328
	(0.0283)
30^{th} percentile	0.0419
	(0.0256)
40^{th} percentile	0.0473*
	(0.0244)
50^{th} percentile	0.0581**
	(0.0235)
60^{th} percentile	0.0672***
	(0.0242)
70^{th} percentile	0.0774***
	(0.0265)
80^{th} percentile	0.0878***
	(0.0301)
90^{th} percentile	0.1061***
	(0.0384)

Legend: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. Standard errors in round brackets.

Table 6 - Marginal effect of university knowledge spillovers for different percentiles of local diversity

	Marginal effect of $UNIKNOW_{i,j}$
$DIVERSITY_j$ at the:	
10^{th} percentile	0.1206***
	(0.0378)
20^{th} percentile	0.1135***
	(0.0326)
30^{th} percentile	0.1008***
	(0.0253)
40^{th} percentile	0.0903***
	(0.0234)
50^{th} percentile	0.0830***
	(0.0248)
60^{th} percentile	0.0767***
	(0.0275)
70^{th} percentile	0.0688**
	(0.0324)
80^{th} percentile	0.0638*
	(0.0361)
90^{th} percentile	0.0580
	(0 .0407)

Legend: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. Standard errors in round brackets.

Appendix

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

Innovative start-up's industry	Cohen et al. (2002) industry	Cohen et al. (2002) scientific fields	Schartinger et al. (2002) industry	Schartinger et al. (2002) scientific fields	University disciplinary areas (MIUR)
Manufacture of computer, electronics and optics products	Computers	Computer science; Mathematics; Electrical engineering; Mechanical engineering	Manufacturing of computers, office machinery	Low level of interaction between scientific fields and industries	Mathematics and computer sciences; Industrial and information engineering
Manufacture of machinery and equipment	Electronic components; Semiconductors and related equipment	Physics; mathematics; electrical engineering; mechanical engineering	Manufacturing of electronics	Low level of interaction between scientific fields and industries	Mathematics and computer sciences; Physics; Industrial and information engineering
Production of software and IT consulting activities	NA	NA	Software and related activities	Other, interdisciplinary technical sciences; Mathematics and informatics	Mathematics and computer sciences; Industrial and information engineering
Telecommunication services	NA	NA	Post and telecommunication services	Electrical engineering	Industrial and information engineering
Business management advisory and management consulting services	NA	NA	NA	NA	Mathematics and computer sciences; Industrial and information engineering; Economics and statistics; Political and Social Sciences
Architecture and engineering activities, Scientific research and development, Other professional, scientific and technical activities	NA	NA	Research & Development	Mining, metallurgy; Economics; Electrical Engineering; Traffic and transport science; Physics, mechanics and astronomy	Physics; Earthsciences; Civil engineering and architecture; Industrial and information engineering; Economics and statistics