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The impact of local and external university knowledge on the creation of knowledge-intensive firms: evidence from the Italian case

Andrea Bonaccorsi · Massimo G. Colombo · Massimiliano Guerini · Cristina Rossi-Lamastra

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Abstract This paper investigates how far in space university knowledge goes to breed the creation of knowledge-intensive firms (KIFs), depending on the nature (either codified or tacit) and quality of this knowledge. We consider the impact of knowledge codified in academic patents and scientific publications and tacit knowledge embodied in university graduates on KIF creation in Italian provinces in 2010, while distinguishing between local university knowledge created by universities located in the same province and external university knowledge created by universities located outside the province. Our econometric estimates indicate that the positive effects of scientific publications and university graduates are confined within the boundaries of the province in which universities are located. Conversely, the creation of new KIFs in a focal province is positively affected by both local and external university knowledge codified in academic patents, even though the positive effect of this external knowledge rapidly diminishes with geographic distance. Furthermore, the above effects are confined to high-quality universities; low-quality universities have little effect on KIF creation.

Keywords Local university knowledge · External university knowledge · Codified knowledge · Tacit knowledge · Creation of knowledge-intensive firms · University quality

JEL classifications I23 · M13 · O33 · O18

1 Introduction

It is commonly known that knowledge has a *limited spatial range*. It spills over the boundaries of the source that produces it and diffuses across space, but its impact decreases with distance. A lively debate has revolved around the issue of *how far in space* various forms of privately and publicly created knowledge produce their effects. Many studies have tried to measure the distance to which knowledge generated at a given point in space exerts an influence on surrounding economic activities (Jaffe et al. 1993; Anselin et al. 1997; Bottazzi and Peri 2003; see Döring and Schnellenbach 2006 for a survey). This literature has traditionally focused on the impact of

A. Bonaccorsi · M. Guerini (✉)
DESTEC, University of Pisa, Largo Lucio Lazzarino, 56122 Pisa, Italy
e-mail: massimiliano.guerini@polimi.it

A. Bonaccorsi
e-mail: a.bonaccorsi@gmail.com

M. G. Colombo · C. Rossi-Lamastra
Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via Lambruschini, 4/B, 20156 Milan, Italy
e-mail: massimo.colombo@polimi.it

C. Rossi-Lamastra
e-mail: cristina1.rossi@polimi.it

knowledge on the innovation activities of incumbent firms, while more recent studies have explored its effect on *new firm creation* (Audretsch and Keilbach 2007; 2008). This paper contributes to this latter research stream by investigating the impact of knowledge produced by universities (referred to hereinafter as university knowledge) on the creation of new knowledge-intensive firms (KIFs) in a geographic area. Focusing on new KIFs adds relevance to our work. The creation of these firms is an important mechanism through which prospective entrepreneurs leverage university knowledge (Mueller 2006; Carree et al. 2012). In addition, scholars unanimously agree that KIFs boost innovation and new job creation and thus play a fundamental role in regional development (Audretsch and Keilbach 2004; 2005; Piergiovanni et al. 2012).

Starting from these premises, the overarching research question addressed in this study is the following: How far in space does university knowledge affect the creation of new KIFs,[1] depending on the *nature* and *quality* of that knowledge? Specifically, in the fulfillment of their three missions (teaching, scientific research, and technology transfer), universities generate both *codified knowledge* (e.g., academic patents and scientific publications) and *tacit knowledge*, which is embodied in university graduates.[2] For each type of knowledge, we distinguish between *local university knowledge* created by universities located in a given geographic area and *external university knowledge* created by universities located outside the area. We test whether local and external academic patents, scientific publications, and graduates have an impact on the creation of new KIFs and how far in space codified and tacit university knowledge extend their effect. As discussed extensively in Sect. 2.2, we expect both local and external university knowledge codified in academic patents and scientific publications to positively affect the creation of new KIFs. In line with mainstream literature (e.g., Anselin et al. 1997), we also expect the effect of external university knowledge to decay with distance. Conversely, the effect of tacit knowledge embodied in university graduates is likely to be confined within the area where universities are located. Finally, we argue that the impact of local and external university knowledge also depends on the quality of the knowledge, as reflected by the quality of the university where the knowledge is created.

In arguing in favor of differences in how far in space tacit and codified university knowledge produce effects on new KIF creation, we add to extant studies, which fail to fully appreciate the consequences of the diverse nature of these three types of university knowledge (see, e.g., Acosta et al. 2011; a notable exception is Belenzon and Schankerman 2013). A further element of originality in our work is the consideration of the quality of university knowledge, an issue that has been largely neglected in the literature.

For our purposes, we combine data from a number of rich information sources, including the EUMIDA database, which contains data on Italian universities, and the MOVIMPRESE directory,[3] which contains the total population of new KIFs established in Italy during 2010. The unit of analysis is the Italian province, which corresponds to level 3 in the Eurostat NUTS classification (*Nomenclature commune des unités territoriales statistiques*, Nomenclature of Territorial Units for Statistics; see Sect. 4 for further details). We estimate negative binomial regression models, with the number of new KIFs in each province as the dependent variable. To assess the impact of local and external university knowledge as a function of the nature of the knowledge, we include among the

[1] For the statistical definition of KIFs, see below. According to the literature, typical examples of KIFs are R&D laboratories, high-tech firms, law and accounting firms, and management, engineering, and computer consultancy companies (Alvesson 1995).

[2] One may contend that academic spin-offs (Rothaermel et al. 2007; Colombo and Piva 2012) and university–industry collaborations (Perkmann et al. 2013) are important mechanisms of knowledge transfer from universities to the productive system that should be taken into account when considering the effects of universities on the creation of new KIFs. However, in this paper, we are explicitly interested in how far in space university knowledge extends its effects, depending on its codified versus tacit nature. As academic spin-offs and university–industry collaborations encompass both the production of tacit (e.g., know-how concerning a production process) and codified knowledge (e.g., a patent), their introduction into the analysis might have confounding effects and lies beyond the scope of this paper. In excluding them from the analysis, we are consistent with mainstream research on the impact of universities on new firm creation at the local level. Indeed, the impact of academic spin-offs and university–industry collaborations has been studied mainly with reference to innovative regional and local activities, while research on knowledge spillovers and new firm creation has largely focused on university knowledge embedded in academic patents, scientific publications, and graduates.

[3] http://www.infocamere.it/movimprese.htm; see Sect. 3 for a detailed description.

independent variables academic patents, scientific publications, and graduates of universities located within and outside the focal province. Different decay rates are envisaged for each type of knowledge. To investigate the role of knowledge quality, we introduce a distinction between knowledge produced by universities that are ranked in the top 40 in Italy, according to the Scimago Institutions Ranking, and knowledge produced by other universities.[4]

Our results show that knowledge codified in academic patents crosses the boundaries of the provinces where the universities that produce it are located, so that *external patents* influence new KIF creation in the focal province. However, this effect rapidly decays with geographic distance. Surprisingly enough, knowledge codified in academic publications is highly localized, its effect being bounded within the boundaries of the province. As expected, the same holds true for knowledge embodied in university graduates. Interestingly, the quality of the university where the knowledge is produced does matter. Specifically, neither local nor external knowledge produced by low-quality universities has any effect on local entrepreneurship. The results described above hold true only for high-quality universities.

The paper is organized as follows. In the next section, we review the literature, provide the conceptual background, and develop theoretical hypotheses. Section 3 describes the data. Section 4 presents the econometric specification and the variables used in the regressions. Section 5 reports the results of the econometric estimates. Section 6 concludes the paper.

2 Conceptual background

2.1 University knowledge and new KIF creation at the local level

The evidence on whether and how university knowledge—codified in scientific publications and academic patents or embodied in university graduates—produces effects on new KIF creation across territories is rather mixed.[5] Using a sample of high-technology start-ups in Germany, Audretsch et al. (2005) found that the location choices of these firms are clearly influenced by the opportunity to access knowledge generated by universities.[6] The authors distinguish between university knowledge in the domains of natural and social sciences. While there is no statistical evidence suggesting that high-tech start-ups locate close to universities to access natural science publications, research indicates that the distance from a university is negatively related to scientific publications in social sciences. In addition, start-ups tend to locate more closely to universities with a large output of graduates in natural sciences. In contrast, this is not true for the social sciences. After controlling for regional characteristics and time effects, Acosta et al. (2011) found that human capital, as measured by the number of university graduates, explains local entrepreneurship in high-tech industries, but found no significant effect of scientific publications or academic patents. The positive effect of university graduates on new firm creation at the local level has also been documented by Armington and Acs (2002), Baptista and Mendonça (2010), and Piva et al. (2011). In their comprehensive analysis, Bonaccorsi et al. (2014) found that graduates, academic staff, and academic patents have strong positive effects on the number of new KIFs in Italian provinces. Conversely, scientific publications have a statistically significant but weakly positive effect.

Although research contributions on the effect of university knowledge on local entrepreneurship have steadily increased, we need to learn more about *how far in space this knowledge produces its effects*. Several studies have addressed this issue with respect to the impact of university knowledge on innovation by *incumbent firms* located in a geographic area. Following the pioneering contribution of Griliches (1979), Anselin et al. (1997) estimated a knowledge production function at the metropolitan statistical area (MSA) level in the USA to evaluate the effect of university and private R&D on the innovative output (i.e., patents and innovation counts) of high-tech firms

[4] http://www.scimagoir.com/. This split corresponds roughly to making a distinction between the top and bottom 50 % of the distribution.

[5] Several studies have found that R&D expenditures by universities have a positive effect on new firm creation at the local level (e.g., Harhoff 1999; Woodward et al. 2006; Kirchhoff et al. 2007).

[6] The authors considered only the effect of the closest university, ignoring the effects engendered by other universities.

located in a focal area. They found that university R&D has an effect in the counties surrounding the MSA, while the effect of private R&D is confined to the same MSA. However, the effect of university R&D is limited to an area within 50 miles of the MSA where the university is located. In 2000, the authors extended their prior work to a sectorally disaggregated level (Anselin et al. 2000a). They found that the effects of university knowledge are industry-specific. No effect was detected in the drug, chemical, and machinery industries, while very strong effects were detected in the electronics and instruments industries. These latter effects were found to extend beyond the boundaries of the MSA by up to 75 miles. This result was confirmed by Varga (2000), who showed, also using US data, that the spatial range of university R&D is up to 75 miles. More recently, Belenzon and Schankerman (2013) analyzed the influence of academic patents and scientific publications on US incumbent firms, as reflected by citations they receive by firms' own patents. The authors found that academic patents are cited in patents by firms located at distances up to approximately 100 miles, and their influence is strongly constrained by state borders. Citations of scientific publications also have a limited spatial range, but they are not constrained by state borders.

To the best of our knowledge, the work by Woodward et al. (2006) is the only study to explicitly focus on the distance up to which university knowledge has an impact on new firm creation. Using data at the US county level, the authors showed that R&D expenditures of universities have a positive influence on new high-tech firm creation up to a distance of approximately 145 miles. The present paper extends this work by arguing that how far in space university knowledge stimulates local entrepreneurship depends on both the *nature* and *quality* of the knowledge generated by universities.

2.2 How far does university knowledge produce effects on the creation of new KIFs? Codified knowledge, tacit knowledge, and knowledge quality

It is a commonly accepted fact that codified knowledge diffuses easily across space. In recent years, advances in information and communication technologies have made its transmission even simpler by enabling low-cost dissemination of documents and files (Song et al. 2007). Accordingly, one might expect university knowledge codified in scientific publications and academic patents to produce effects that cross the boundaries of the province where the knowledge is produced and affect the creation of new KIFs in distant provinces. This does not mean that distance has no influence on codified knowledge. Theoretically, academic patents and scientific publications are *accessible* from everywhere and have the potential to benefit prospective entrepreneurs at long distance. However, we claim that prospective entrepreneurs' ability to leverage codified university knowledge when creating their new ventures is negatively affected by the distance from universities producing it. Indeed, in order for this knowledge to be *effectively absorbed* (Cohen and Levinthal 1990) by prospective entrepreneurs, it must be used in combination with the *specific knowledge* possessed by its creators, i.e., academic personnel authoring publications and filing patents. This specific knowledge is largely tacit and is thus hardly transmissible. It can be leveraged by *direct interactions* (Morgan 2004), which are enabled by geographic proximity between university personnel and prospective entrepreneurs.

From the above arguments, we conclude that not only local university knowledge codified in academic patents and scientific publications but also external knowledge produce effects on new KIF creation in a focal province. However, the effect of external university knowledge decays with distance. Hypothesis H1 and H2 follow.

H1 Both local and external university knowledge codified in academic patents and scientific publications have positive effects on the creation of new KIFs in a focal province.

H2 The positive effect of external university knowledge codified in academic patents and scientific publications on the creation of new KIFs in a focal province decays with distance.

Furthermore, we argue that the knowledge decay for scientific publications is different from that for academic patents, with the former being more sensitive to distance than the latter. Scientific publications expand the pool of knowledge upon which technical advances of commercial value can be built (Fleming and Sorenson 2004). However, knowledge codified in scientific publications is still fluid and partially formed and rarely has an *immediate* industrial application (e.g., Stephan 2012). Therefore, we expect that, to successfully leverage this knowledge in the creation of a new firm, a prospective entrepreneur requires more intense and frequent direct interactions with academic personnel than when exploiting an academic patent. Cohen et al. (2002) provided support for this view in their investigation of how public research from university impacts industrial R&D. They found that direct interactions complement academic publications in favoring the assimilation of knowledge codified in scientific publications. This does not happen in the case of academic patents that codify university knowledge in an advanced stage of development and are more suitable for commercial applications. On the basis of these arguments, we put forth hypothesis H3.

H3 The positive effect of external university knowledge codified in scientific publications on the creation of new KIFs in a focal province decays with distance at a higher rate than the effect of external university knowledge codified in academic patents.

Let us now turn our attention to tacit university knowledge embodied in graduates. New KIF creation at the local level is stimulated by the local availability of university graduates, who can found new KIFs (Astebro et al. 2012) or be hired by newly created KIFs (Piva et al. 2011). We predict that tacit university knowledge embodied in graduates is highly localized, its effects being limited to the province where it is produced. In other words, while local tacit university knowledge has an impact on new KIF creation, external tacit university knowledge does not.

Numerous studies have shown that prospective entrepreneurs prefer to locate their new ventures in areas where they have lived, i.e., where they have worked as employees and/or where they were born (Figueiredo et al. 2002; Parwada 2008; Buenstorf and Klepper 2009; evidence in the Italian case is presented in Michelacci and Silva 2007). Prospective entrepreneurs have developed friendships and professional relations in these areas, while their family and relatives usually live in close proximity. These personal networks cause *emotional attachment* to areas where prospective entrepreneurs have lived, this being an important driver of firms' location choices (Dahl and Sorenson 2009).

Furthermore, in the difficult start-up phase of a new venture, personal networks are of great help in raising financial resources, recruiting employees, and attracting customers (Sorenson and Audia 2000; Stam 2007). Expanding on these arguments, we posit that graduates from a university located in a province are more prone to establish their new ventures in that province than in other locations. First, university graduates may reside with their families in the province in which their alma mater (i.e., the university from which they graduated) is located. Alternatively, they can come from other provinces. In both cases, the university experience constitutes a milestone in the formation of their personal networks (Baltzopoulos and Broström 2013).[7] When attending university, students develop connections with classmates, university professors, and more generally with the local community. These personal networks are established in the most formative years of an individual's life. The emotional attachment and social capital that these personal networks generate are important enough to drive the choice of locating a venture in the province of the alma mater. Empirical evidence supports our reflections. Using a comprehensive Swedish database, Baltzopoulos and Broström (2013) found that entrepreneurs exhibit an increased propensity to start their new ventures in the places where they graduated.

Like graduate entrepreneurs, university graduates who do not establish a new firm themselves prefer to join (new) firms located in the province of their alma mater (e.g., Huffman and Quigley 2002; Hoare and Corver 2010). In so doing, they can leverage the aforementioned personal and professional networks that they have developed during their university studies. Moving elsewhere would disrupt their emotional attachment to the location of their alma mater.

In summary, although the role of universities in individuals' mobility has not been well researched (Drucker and Goldstein 2007), the discussion above indicates that universities are attractors of talents who are inclined to stay in the area of their alma mater after graduation. This general inclination is even stronger in Italy, a country in which individuals' mobility across

[7] According to Baltzopoulos and Broström (2013), this is particularly true for students who choose to relocate to attend a specific university. They find themselves in new environments and have the chance to build entirely new social networks.

space is traditionally low (Addario and Vuri 2010). As university graduates are likely to remain near their alma mater when founding a new venture or finding a job, the tacit knowledge they embody is leveraged mainly in new KIFs located in the surroundings of their universities. Hypothesis H4 follows.

H4 Local tacit university knowledge embodied in university graduates has a positive effect on the creation of new KIFs in a focal province, while external tacit university knowledge does not.

Finally, we envisage that the spatial extent to which university knowledge influences local entrepreneurship depends on knowledge *quality*, as reflected by the quality of universities that produce it. The impact of university quality on knowledge spillovers has not been thoroughly explored. In a recent contribution, Laursen et al. (2011) showed that incumbent firms' decisions to collaborate with universities are influenced by both geographic proximity and university quality. Being located close to a high-quality university (i.e., within 100 miles) increases the propensity for firms to collaborate locally. Conversely, closeness to a low-quality university discourages local collaborations. In the absence of a high-quality university nearby, the second-best choice is to collaborate with a distant high-quality university (i.e., one that is more than 100 miles away). In other words, firms appear to prefer university quality over geographic proximity, in line with the view that the benefits of leveraging high-quality knowledge outweigh the costs of long-distance collaboration.

We argue that the results of Laursen et al. related to university–industry relations can be extended to new firm creation. Accordingly, we predict that *codified knowledge* produced by *high-quality* universities has positive effects on the creation of new KIFs, both locally and in distant areas, exerting its beneficial influence outside the province where it is created. As the mobility of individuals is normally low, prospective entrepreneurs residing in areas that are distant from high-quality universities might not be willing to move closer to these universities to found their ventures. However, they may want to leverage the codified knowledge that these highly reputed universities produce. Indeed, as the findings of Laursen et al. suggest with respect to incumbent firms, the expected benefits of using this knowledge exceed the (high) cost of accessing it over long distances.

In addition, we argued above that university graduates are more likely to establish a firm or find a job in a new firm located in the province in which their alma mater is located than to move elsewhere. This is especially true for high-quality universities, due to the high quality of the networks developed by graduates. Therefore, we expect high-quality tacit university knowledge to have a positive effect on the creation of new KIFs, being concentrated locally. We therefore derive hypotheses H5 and H6.

H5 Both local and external university knowledge codified in academic patents and scientific publications produced by high-quality universities have positive effects on the creation of new KIFs in a focal province.

H6 Local tacit university knowledge embodied in the graduates of high-quality universities has a positive effect on the creation of new KIFs in the focal province where these universities are located, while high-quality external tacit university knowledge does not.

Conversely, we expect the benefits of using knowledge created by low-quality universities to be low regardless of the type of knowledge (either codified or tacit) and the locations of the universities that produce the knowledge. Accordingly, we formulate hypothesis H7.

H7 University knowledge created by low-quality universities has a negligible effect on the creation of new KIFs, both in the focal provinces where these universities are located and elsewhere.

3 Econometric models

3.1 Model specification

To assess the impact of local and external university knowledge on new KIF creation, we estimate various models, with the number of new KIFs in a geographic area (i.e., an Italian province; see Sect. 4 for further details) as the dependent variable. The independent variables include a set of explanatory variables that account for the different types of university knowledge and a set of control variables related to territorial characteristics. Because university knowledge variables are highly correlated (see Table 3 in Sect. 4), we run separate regressions to avoid multicollinearity problems. We estimate various models with the following general form:

$$\mathrm{NewKIFs}_i = \exp\left(\alpha + \beta_1 \log x_i^{\mathrm{local}} + \beta_2 \log x_i^{\mathrm{external}} + \partial Z_i + \varepsilon_i\right), \quad (1)$$

where ε_i denotes unobserved effects.[8] The dependent variable $\mathrm{NewKIFs}_i$ is the number of new KIFs established during 2010 in province i. The variables x_i^{local} and x_i^{external} refer to the types of university knowledge (patents, publications, and graduates) generated inside and outside province i, respectively. Given the logarithmic transformation of x_i^{local} and x_i^{external} and the exponential specification of Eq. (1), the coefficients of these variables are to be interpreted as elasticities.

More specifically, the variables x_i^{local} refer to the total number of patent applications ($\mathrm{Patents}_i^{\mathrm{local}}$), scientific publications ($\mathrm{Publications}_i^{\mathrm{local}}$),[9] and graduates ($\mathrm{Graduates}_i^{\mathrm{local}}$) produced by all universities located in province i. Conversely, the variables x_i^{external} refer to external university knowledge, i.e., academic patents, scientific publications, and graduates produced by universities located outside province i. In line with mainstream literature (e.g., Anselin et al. 1997), we assume that the effect of external university knowledge on new firm creation in province i decays with the distance between province i and the province j where this knowledge is produced. Accordingly, we use a spatially weighted measure of the following type:

$$x_i^{\mathrm{external}} = \sum_{j \neq i} \frac{x_j^{\mathrm{local}}}{d_{i,j}^{\alpha}}, \quad (2)$$

where $d_{i,j}$ is the distance between the focal province i and province j, x_j^{local} is the knowledge (i.e., the number of patent applications, publications, and graduates) generated by universities located in province j (with $j \neq i$), and α is a distance decay parameter. Distances were calculated by considering the centroid of each province (we use 10 km as the unit of distance). The decay parameter α depends on the type of knowledge considered. Specifically, for each type of university knowledge, we set α to the value that maximizes the log-likelihood of the econometric model in which the type of university knowledge is the independent variable. A detailed description of the procedure we used to estimate decay parameter values is given in Appendix 1. According to this procedure, decay parameter values of 1.7, 4.6, and 4.4 were obtained for patents, publications, and graduates, respectively.

The vector Z_i includes several control variables that account for factors that affect new KIF creation at the local level other than those related to university knowledge. First, agglomeration effects may arise from the presence of other firms (e.g., Baptista and Swann 1999; Acs and Plummer 2005). Therefore, we considered the ratio of the number of incumbent firms (in all industries) to the number of employees in province i ($\mathrm{Incumbents/Employees}_i$).[10] We also included a variable for the number of incumbent KIFs as a percentage of the total number of incumbent firms (in all industries) in province i ($\mathrm{KIFs/Incumbents}_i$). We expect these variables to have positive effects on new KIF creation in the province. Second, to account for demand effects, we considered the ratio between the value added and the number of employees in province i ($\mathrm{VA/Employees}_i$) and the population density ($\mathrm{PopDensity}_i$), as measured by the population of province i per square meter. Third, unemployed individuals may be more likely to start their own firms because the opportunity costs of self-employment are low (for a discussion of this issue see, e.g., Carree et al. 2008). To control for this effect, we included the variable $\mathrm{Unemployment}_i$, which represents the number of unemployed individuals as a percentage of the total workforce in province i. Fourth, we included a dummy variable indicating whether there is at least one business incubator (BI_i) in province i. Business incubators assist nascent firms in developing their businesses and provide support services to them (Colombo and Delmastro 2002). Therefore, a positive effect on the creation of new KIFs is envisaged. Fifth, we considered the area of each province (measured in 1,000s of square kilometers) to control for size effects (Size_i). Finally,

[8] We use an exponential specification because we assume that the dependent variable follows a negative binomial distribution. See Sect. 3.2 for further details.

[9] As explained in Sect. 4, we do not consider the raw count of publications but rather an alternative measure obtained by weighting publications depending on the research areas to which they belong.

[10] One might expect agglomeration externalities to extend far beyond the border of a province. In Sect. 5.3, we describe how we control for this effect.

provinces that are close to national borders may benefit from knowledge generated by universities located abroad. Alternatively, the rate of new KIF creation may be lower than expected in these provinces if entrepreneurs are attracted abroad by more favorable institutional or fiscal environments. Hence, we control for national border proximity by including a dummy variable that equals 1 if the province is located close to a national border (Border_i).[11]

It is worth noting that the specification introduced with Eq. (1) does not permit evaluation of whether high-quality universities produce stronger effects on new KIF creation. To this end, we employ Eq. (3):

$$\begin{aligned}\text{NewKIFs}_i = \exp(\alpha + \gamma_1 \log x\text{HQ}_i^{\text{local}} \\ + \gamma_2 \log x\text{HQ}_i^{\text{external}} + \gamma_3 \log x\text{LQ}_i^{\text{local}} \\ + \gamma_4 \log x\text{LQ}_i^{\text{external}} + \partial Z_i + \varepsilon_i).\end{aligned} \tag{3}$$

Equation (3) distinguishes between knowledge produced in high-quality universities and knowledge produced in low-quality universities.[12] Thus, for each type of knowledge (patents, publications, and graduates), the variables $x\text{HQ}_i^{\text{local}}$ and $x\text{HQ}_i^{\text{external}}$ refer to knowledge produced by the universities among the top 40 Italian universities that are inside and outside province i, respectively. Conversely, the variables $x\text{LQ}_i^{\text{local}}$ and $x\text{LQ}_i^{\text{external}}$ refer to knowledge produced by other Italian universities.

3.2 Methodology

We employ negative binomial regressions to estimate Eqs. (1) and (3). The underlying assumption is that the number of new KIFs in a province can be interpreted as count data (e.g., Audretsch and Lehmann 2005; Abramovsky et al. 2007). The simplest form of a count data model is one in which the dependent variable follows a Poisson distribution, so its variance is set equal to the mean. Nevertheless, in cases where there is overdispersion, i.e., where the variance is greater than the mean, the Poisson variance assumption does not hold (Cameron and Trivedi 1990). The negative binomial model provides a useful generalization of the Poisson model and is well suited to data characterized by overdispersion (Greene 2003). To evaluate the appropriateness of the negative binomial regression model, we performed a likelihood ratio test of the null hypothesis that the overdispersion coefficient is zero. The null hypothesis is rejected at a significance level of 1 %, indicating that the negative binomial model is preferred over the Poisson model (the results of the test are available from the authors upon request).

To alleviate possible endogeneity[13] concerns, the university variables and the control variables are lagged with respect to NewKIFs_i. As explained in the next section, the data on new KIFs pertain to 2010, the data on university and on territorial characteristics of Italian provinces pertain to 2008, and the data on incumbent KIFs pertain to 2009. Finally, we control for intraregional correlation by adding dummy variables at NUTS level 1 and clustering data at NUTS level 2 (for a similar approach, see Baptista and Mendonça 2010).

4 Data and descriptive evidence

To test our hypotheses, we used data collected from several sources and classified the locations of the new KIFs and the universities into 103 geographical units (i.e., Italian provinces, equivalent to the Eurostat NUTS level 3).[14]

The data on Italian KIFs were extracted from the MOVIMPRESE database, which provides information on all new firms established in Italy every year and on the population of incumbent firms. The data include the industry of activity (NACE rev. 2 classification at the

[11] The variable Border_i equals zero if the province shares borders with one of the two enclaves within the Italian territory, i.e. Republic of San Marino and Vatican City State.

[12] Because in some provinces (11) there are both high- and low-quality universities, we cannot specify interaction terms in the model, discriminating between provinces with high- and low-quality universities.

[13] However, as a robustness check, we also run instrumental variable regressions to estimate Eqs. (1) and (3). See Sect. 5.3 for a detailed description.

[14] The NUTS classification is a hierarchical system for dividing up the economic territory of the EU. It subdivides each member state into NUTS level 1, level 2, and level 3 territorial units (for further information, see http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction). In Italy, NUTS level 3 units correspond to intermediate administrative divisions (*provincie*). During the period 2005–2009, seven new provinces were created (Olbia–Tempio, Ogliastra, Medio Campidano, Carbonia–Iglesias, Monza–Brianza, Fermo, and Barletta–Andria–Trani). Therefore, the current number of Italian provinces is 110. However, data on new KIFs and on territorial characteristics are not available for these new provinces.

two-digit level) and the location of every firm at NUTS level 3. Based on industry data, we first defined knowledge-intensive industries.[15] Then, we extracted data for new KIFs in 2010 and for incumbent KIFs in 2009. In 2010, 4,761 new KIFs were established in Italy.[16]

Data on universities were collected from three sources. First, we extracted information on university graduates and academic patent applications in 2008 from the EUMIDA database. This database was developed under a European Commission tender and is based on official statistics produced by national statistical authorities in all 27 EU countries plus Norway and Switzerland (for details, see European Commission 2010). It contains information on 2,457 European higher education institutions. Of these, 1,364 are defined as research-active institutions, including universities (institutions that confer PhD degrees) and other non-university institutions. The *research-active* label implies that research is considered by the higher education institution as a constitutive part of its institutional activities and it is organized with a durable perspective.[17] We considered the 80 research-active universities located in Italy. Second, data on academic publications were hand-collected from the Web of Knowledge database, a database administered by the Institute for Scientific Information (ISI). For each research-active university, we collected data on all publications that appeared in ISI scientific journals from 2000 to 2008. However, instead of using the raw number of publications, we computed a measure that accounts for the differences in the frequency of publication in each of the 151 research areas listed in ISI (details of the methodology used are available in Appendix 3). Indeed, the relation between research activity and publication frequency varies across scientific fields (e.g., clinical medicine and biomedicine dominate raw counts of academic publications; see Glänzel 2000). Using this approach, the allegedly positive impact of knowledge codified in publications on new KIF creation should not be related differences in access to expertise in those fields.[18] Data on publications were then aggregated at NUTS level 3 (Italian provinces). Third, to assess university quality, we consulted the 2010 edition of the Scimago Institutions Ranking, which includes 2,833 research-active institutions from all around the world, grouped into institutional sectors and world regions. The ranking includes four key performance indicators to evaluate institutions' outcomes in terms of research size, performance, impact, and internationalization (Scimago 2010). We considered as high-quality universities those belonging to the top 40 Italian universities.[19]

Control variables refer to an array of territorial characteristics of Italian provinces. First, we used databases of the Italian National Institute of Statistics (ISTAT) to extract the total population, the area in

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[15] See Appendix 2 for the list of knowledge-intensive industries included in the sample.

[16] It is likely that some of the KIFs created during 2010 are academic spin-offs. Unfortunately, we do not have data on the exact localization of these academic spin-offs, and so we cannot exclude them from the sample to check whether their presence affects our results. This is undoubtedly a limitation of the present analysis. However, given the low number of spin-offs with respect to the total number of new KIFs, it is very unlikely that their presence would bias our results. According to the NETVAL report (NETVAL 2012), in Italy in 2010, 117 academic spin-offs were founded across all industries, representing 2.5 % (117/4,716) of the total number of new KIFs in 2010.

[17] Criteria for inclusion were the following: the existence of institutionally recognized research units, the existence of an official research mandate, the presence of regular PhD programs, the consideration of research in strategic objectives and plans, and the regular funding of research projects by public agencies or private companies. See Bonaccorsi et al. (2012) for a more detailed description and full-scale analysis of these data.

[18] We thank one of the anonymous reviewers for raising this important point.

[19] Scimago is generally considered a reliable source of data for comparative analysis because it does not measure only publications in top journals or by highly cited scientists but rather covers a wider range of publications. Nevertheless, being based on international publications, it clearly underestimates the quality of research in the humanities and social sciences, in which a larger share of output is published in books and national-language journals. We consider this limitation acceptable because the research production most relevant to new KIF creation, as shown in Bonaccorsi et al. (2014), is from scientific and technical fields, which are well covered by the raw Scimago data. Another limitation is that the Scimago rankings of institutions are based on four indicators, three of which are independent of size (percentage of international collaborations, normalized impact score, and percentage of publications in high-quality journals) and one of which (number of publications) is not (see http://www.scimagoir.com/methodology.php?page=indicators for details). This may explain why some small high-quality Italian universities do not appear in the top 40 list. For these reasons, use of the label "high-quality" or "low-quality" does not imply at all an overall evaluation but is rather a convenient shorthand for comparing universities with respect to research production in fields that are well covered by the Scimago data and are most relevant to new KIF creation.

square meters, the unemployment rate, and the value added in thousands of Euros in 2008 for each Italian province. Second, we downloaded the list of Italian science parks and business incubators from the website of the Association of Italian Science and Technology Parks (APSTI, see http://www.apsti.it).

Figure 1 illustrates the geographic distribution of new KIFs per square km (map 1, on the left) and the geographic distribution of university knowledge across provinces (map 2, on the right), estimated as the principal component of patents, publications, and graduates. Map 1 reveals a high concentration (the darkest areas) of new KIFs per square km in the north of Italy. Map 2 shows a more uniform distribution of university knowledge across Italian provinces (in 51 of 103 provinces, there is at least one university). The darkest areas (higher levels of university knowledge) correspond mainly to provinces with more than one university (15 of the 51 provinces with at least one university). These are mainly provinces that include large metropolitan areas such as Milan, Rome, Naples, and Turin. However, higher levels of university knowledge are also associated with smaller provinces with just one university, such as Bologna and Padova.

Table 1 presents some descriptive statistics on the number of patents, publications, and graduates produced by Italian universities. The table distinguishes between high-quality and low-quality Italian universities, according to the Scimago Institutions Ranking. The statistics in Table 1 clearly highlight the relationship between the production of university knowledge and the quality of universities. On average, a high-quality Italian university (i.e., a university in the top 40 Italian universities according to the Scimago 2010 ranking) produced 4.77 patents and 6.12 thousand graduates in 2008 and 7.38 thousand publications in the period 2000–2008. The corresponding values for a low-quality university are 0.35, 1.19, and 1.11, respectively. All these differences are statistically significant at the 1 % level.

Table 2 presents descriptive statistics of the variables used in the regressions, and Table 3 presents the correlation matrix.

5 Results

5.1 Main results

In this section, we illustrate the results of the negative binomial regressions, with the number of new KIFs as the dependent variable. Table 4 presents the results of the negative binomial regressions of Eq. (1). The first two columns show the results concerning the impact of codified knowledge (patents in column I and publications in column II) on the creation of new KIFs. Column III shows the results concerning the impact of tacit knowledge embodied in individuals (i.e., university graduates).

The control variables Incumbents/Employees$_i$, VA/Employees$_i$, Border$_i$, and Size$_i$ are highly significant (at the 1 % level, in most cases) in all regressions. Hence, we find evidence that the creation of new KIFs is influenced by agglomeration effects associated with the presence of incumbents, demand effects, size, and national border proximity, with the last of these having a negative effect. The coefficient of BI$_i$, which reflects the presence in the focal province of one or more business incubators, is positive but has generally lower statistical significance than the above-mentioned control variables. Finally, we find positive evidence (significant at the 5 % level) of the presence of agglomeration effects due to incumbent KIFs (KIFs/Incumbents$_i$) in columns II and III but not in column I (where the coefficient is positive but not significant).

We now turn our attention to university variables. Column I shows that university knowledge codified in patents positively affects new KIF creation at the local level. Indeed, the coefficient of $\text{Patents}_i^{\text{local}}$ is positive and significant at the 5 % level. We find that $\text{Patents}_i^{\text{external}}$ also has a positive and significant effect. The impact of these variables is not only significant but also of large economic magnitude. As mentioned in Sect. 3.1, given the logarithmic transformation of university variables and the exponential specification, the coefficients of these variables are elasticities that indicate the average percentage change in the number of new KIFs in a province for a 1 % change in the explanatory variable. Hence, a 1 % increase in $\text{Patents}_i^{\text{local}}$ leads to an expected increase in the number of new KIFs of 0.25 %. To correctly interpret the coefficient of $\text{Patents}_i^{\text{external}}$, we should take into account the distance from the focal province and the decay parameter associated with this type of university knowledge (i.e., $\alpha = 1.7$). Accordingly, a 1 % increase in the number of patents at a distance of 15 km (the minimum distance among provinces in our data is indeed 15 km) corresponds to a 0.28 % increase in the

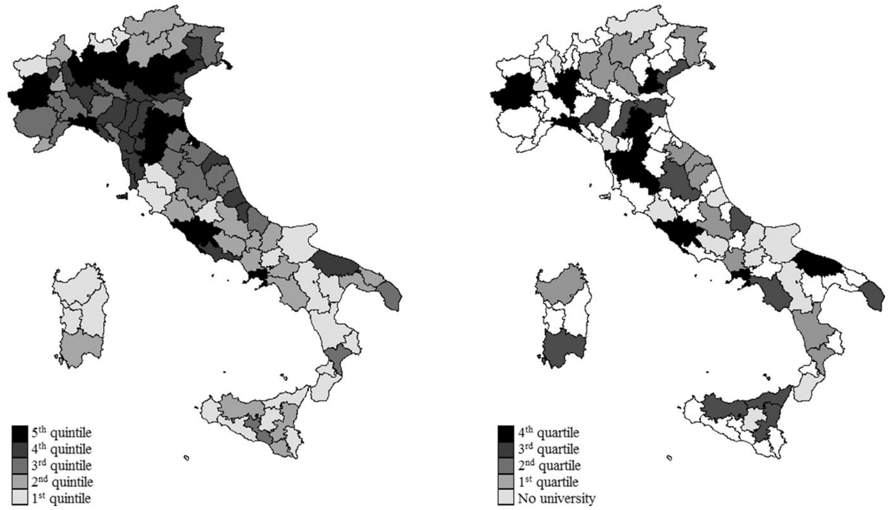

Fig. 1 New KIFs per square km and university knowledge. *Notes* Data on new KIFs are for 2010. University knowledge is calculated as the principal component of academic patents, scientific publications, and graduates. Data on patents and graduates are for 2008. Data on publications are for the period 2000–2008 and were obtained according to the procedure described in Appendix 3

number of new KIFs in the focal province (i.e., 0.56 %/$1.5^{1.7}$). This value is qualitatively similar to the increase associated with $\text{Patents}_i^{\text{local}}$ (0.25 %). However, the positive effect of academic patents rapidly diminishes with increasing distance, as shown in Fig. 2, which illustrates the expected percentage increase in the number of new KIFs in the focal province due to a 1 % increase in the number of patents. The bold and dotted lines represent the increase in the number of new KIFs associated with 1 % increases in $\text{Patents}_i^{\text{local}}$ and $\text{Patents}_i^{\text{external}}$, respectively. The values shown in the figure are calculated on the basis of the estimated coefficients of Eq. (1) reported in Table 4. At distances of 20, 50, and 100 km, a 1 % increase in the number of academic patents leads to increases of 0.17, 0.04, and 0.01 %, respectively, in the number of new KIFs in the focal province.

These results demonstrate that, in line with H1 and H2, both local and external university knowledge codified in patents have positive effects on the creation of new KIFs in the focal province and that the effect of external university knowledge rapidly decays with distance. Conversely, in examining the effects of knowledge codified in publications (column II) and tacit knowledge embodied in graduates (column III), a different picture emerges. Indeed, the coefficients of $\text{Publications}_i^{\text{local}}$, $\text{Publications}_i^{\text{external}}$, $\text{Graduates}_i^{\text{local}}$, and $\text{Graduates}_i^{\text{external}}$ are not significant. Thus, for knowledge codified in publications we do not find support for H1. However, the fact that we do not detect any role for external university knowledge associated with publications and graduates is in line with H3 and H4.[20]

We now turn our attention to the analysis of the difference between high- and low-quality universities. Table 5 reports the results of the negative binomial regressions of Eq. (3). Here we evaluate whether university quality affects the impact of the different types of university knowledge. Again, the first two columns show the results concerning codified knowledge (patents in column I and publications in column II), and column III shows the results for the impact of tacit knowledge embodied in graduates.

The magnitudes and statistical significance of the coefficients of the control variables shown in Table 5 remain substantially unchanged from those shown in Table 4. The results in Table 5 for the university variables exhibit a very clear pattern. First, in line with H7, knowledge produced by low-quality universities turns out to have a negligible impact on the creation of new KIFs, independent of the type of knowledge (either codified or tacit) and the locations of these universities.[21] Second, in examining the effects of

[20] The LR test reported at the bottom of Table 4 confirms that including $\text{Patents}_i^{\text{external}}$ in the regression significantly improves the log-likelihood with respect to a restricted model in which $\text{Patents}_i^{\text{external}}$ is set to zero. Conversely, the LR tests concerning $\text{Publications}_i^{\text{external}}$ and $\text{Graduates}_i^{\text{external}}$ do not reject the null hypothesis that the values of these latter variables are equal to zero.

[21] The LR test results reported at the bottom of Table 5 confirm that including $x\text{LQ}_i^{\text{local}}$ and $x\text{LQ}_i^{\text{external}}$ in the regression does not significantly improve the log-likelihood with respect to a

Table 1 Type of university knowledge and university quality

Type of university knowledge	Number of observations	Mean	SD	Min.	Max.
Italian universities					
Number of patents	80	2.56	7.01	0	56
Number of publications (thousands)	80	4.25	5.34	0	23.67
Number of graduates (thousands)	80	3.66	3.76	0	19.70
High-quality Italian universities					
Number of patents	40	4.77	9.44	0	56
Number of publications (thousands)	40	7.38	5.96	0.72	23.67
Number of graduates (thousands)	40	6.12	3.89	1.40	19.70
Low-quality Italian universities					
Number of patents	40	0.35	0.66	0	2
Number of publications (thousands)	40	1.11	1.44	0	7.41
Number of graduates (thousands)	40	1.19	1.01	0	4.22

The high-quality Italian universities are the top 40 Italian universities ranked in the Scimago Institutions Ranking (2010). The low-quality Italian universities are the remaining Italian universities active in research. Data on patents and graduates are for 2008. Data on publications are for the period 2000–2008 and were obtained according to the procedure described in Appendix 3

high-quality university knowledge, we find that both codified and tacit knowledge produced by high-quality universities have positive and significant impacts on the creation of new KIFs in the provinces where these universities are located. The coefficient of PatentsHQ$_i^{\text{local}}$ is positive and significant at the 5 % level, while the coefficients of PublicationsHQ$_i^{\text{local}}$ and GraduatesHQ$_i^{\text{local}}$ are positive and significant at the 10 % level. However, while the patent elasticity is of considerable magnitude—a 1 % increase in the number of patents of local high-quality universities leads to an increase of 0.23 % in the number of new KIFs in the focal province—the magnitudes of the effects of publications and graduates are small, with both elasticities being equal to 0.03 %. Third, PatentsHQ$_i^{\text{external}}$ has a positive effect on new KIF creation that is significant at the 5 % level. The magnitude of this effect is similar to the magnitude of the effect of Patents$_i^{\text{external}}$ reported in Table 4. Conversely, the coefficients of PublicationsHQ$_i^{\text{external}}$ and GraduatesHQ$_i^{\text{external}}$ are not significant. These results are in line with H5 (for patents but not for publications) and H6.

5.2 Additional evidence on academic patents

The results shown in the previous section highlight the fact that the effect of external university knowledge codified in academic patents by high-quality universities decays with distance. However, the specification introduced with Eq. (3) does not permit identification of the distance threshold beyond which this effect is not significant. To this end, instead of distinguishing between local and external university knowledge, we defined the following variables: PatentsHQ$_i^{<K}$, PatentsHQ$_i^{>K}$, PatentsLQ$_i^{<K}$, and PatentsLQ$_i^{>K}$. Specifically, PatentsHQ$_i^{<K}$ includes both high-quality university patents produced in province i and the spatially weighted sum of high-quality university patents produced outside province i (with the decay parameter value being 1.7) up to a distance K. Conversely, PatentsHQ$_i^{>K}$ includes the spatially weighted sum of patents produced outside province i beyond the distance K. PatentsLQ$_i^{<K}$ and PatentsLQ$_i^{>K}$ refer to low-quality university patents and are defined in a similar way. Table 6 reports the estimates related to the impact of university knowledge codified in patents for various values of K (20, 30, 40, 50, 60, 70 km).

The results given in Table 6 clearly show that beyond 50 km the impact of high-quality university patents generated outside province i is not significant. For $K < 50$ km (columns I–III) the coefficients of PatentsHQ$_i^{>K}$ are positive and significant at the 1 % level, and for $K = 50$ km, PatentsHQ$_i^{>50}$ (column IV) is positive and significant at the 5 % level, but for $K > 50$ km the

Footnote 21 continued
restricted model in which these variables are set to zero (for all types of university knowledge). Hence, we cannot reject the null hypothesis that the impact of knowledge (both local and external) produced by low-quality universities is zero.

Table 2 Summary statistics for regression variables

Variable	Obs.	Mean	SD	Min.	Max.
NewKIFs$_i$	103	46.22	105.86	1.00	1,008.00
Incumbents/Employees$_i$	103	50.32	14.25	21.06	92.66
KIFs/Incumbents$_i$	103	11.09	2.21	6.73	19.09
VA/Employees$_i$	103	57.20	6.61	45.46	79.30
Unemployment$_i$	103	7.86	3.71	2.13	17.94
Border$_i$	103	0.15	0.35	0.00	1.00
Size$_i$	103	2.93	1.75	0.21	7.68
PopDensity$_i$	103	0.25	0.34	0.04	2.63
BI$_i$	103	0.39	0.49	0.00	1.00
Patents$_i^{\mathrm{local}}$	103	0.45	0.83	0.00	4.09
Patents$_i^{\mathrm{external}}$	103	0.80	0.39	0.17	1.71
PatentsHQ$_i^{\mathrm{local}}$	103	0.38	0.82	0.00	4.09
PatentsHQ$_i^{\mathrm{external}}$	103	0.76	0.40	0.15	1.69
PatentsLQ$_i^{\mathrm{local}}$	103	0.08	0.26	0.00	1.10
PatentsLQ$_i^{\mathrm{external}}$	103	0.08	0.06	0.01	0.37
Publications$_i^{\mathrm{local}}$	103	3.97	4.18	0.00	10.66
Publications$_i^{\mathrm{external}}$	103	1.93	1.35	0.01	6.53
PublicationsHQ$_i^{\mathrm{local}}$	103	2.87	4.14	0.00	10.46
PublicationsHQ$_i^{\mathrm{external}}$	103	1.73	1.35	0.00	6.53
PublicationsLQ$_i^{\mathrm{local}}$	103	1.70	3.01	0.00	9.00
PublicationsLQ$_i^{\mathrm{external}}$	103	0.63	0.79	0.00	3.50
Graduates$_i^{\mathrm{local}}$	103	3.98	4.17	0.00	10.54
Graduates$_i^{\mathrm{external}}$	103	2.11	1.27	0.01	6.28
GraduatesHQ$_i^{\mathrm{local}}$	103	2.83	4.08	0.00	10.37
GraduatesHQ$_i^{\mathrm{external}}$	103	1.86	1.28	0.01	6.28
GraduatesLQ$_i^{\mathrm{local}}$	103	1.63	3.08	0.00	8.72
GraduatesLQ$_i^{\mathrm{external}}$	103	0.75	0.88	0.00	3.73

All university variables are in logarithms

coefficients of PatentsHQ$_i^{>K}$ (columns V–VII) are not significant at conventional confidence levels.

5.3 Robustness checks

To further validate our findings, we run three robustness checks (the results of which are presented in Tables 8 and 9 in Appendix 4). First, we checked whether the positive effect of PatentsHQ$_i^{\mathrm{external}}$ on new KIF creation in the focal province is biased because of the presence of other agglomeration externalities in the area surrounding this province. Accordingly, in the estimation of Eq. (3), we added the ratio of the number of incumbents in other provinces, up to a distance of 200 km from province i, to the number of employees in these provinces (Incumbents/Employees$_i^{200}$). If the coefficient of this additional control variable was found to be positive and significant and if at the same time PatentsHQ$_i^{\mathrm{external}}$ lost its significance, one might infer that the results reported in Table 5 are affected by an omitted variable bias. In fact, what was interpreted as the effect of external university knowledge codified in patents on new KIF creation would be driven instead by other agglomeration externalities in the area surrounding the focal province. This additional control was not significant, and the results substantially confirmed the findings reported in Table 5.

Second, instead of the negative binomial regression model, we run ordinary least squares (OLS) estimations with a semi-log specification (i.e., the dependent

Table 3 Correlation matrix for regression variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	$NewKIFs_i$	1.00												
(2)	$Incumbents/Employees_i$	0.46	1.00											
(3)	$KIFs/Incumbents_i$	0.46	−0.09	1.00										
(4)	$VA/Employees_i$	0.54	0.60	0.34	1.00									
(5)	$Unemployment_i$	−0.16	−0.50	0.04	−0.62	1.00								
(6)	$Border_i$	−0.01	0.07	−0.04	0.24	−0.29	1.00							
(7)	$Size_i$	0.04	−0.23	0.12	−0.07	0.18	0.03	1.00						
(8)	$PopDensity_i$	0.60	0.52	0.27	0.40	0.02	0.01	−0.27	1.00					
(9)	BI_i	0.23	0.19	0.26	0.27	−0.08	−0.05	0.08	0.24	1.00				
(10)	$Patents_i^{local}$	0.60	0.25	0.50	0.42	−0.07	−0.06	0.21	0.34	0.39	1.00			
(11)	$Patents_i^{external}$	0.04	0.45	−0.25	0.27	−0.60	0.09	−0.36	0.04	−0.03	−0.13	1.00		
(12)	$PatentsHQ_i^{local}$	0.62	0.27	0.51	0.44	−0.08	−0.02	0.18	0.36	0.36	0.95	−0.11	1.00	
(13)	$PatentsHQ_i^{external}$	0.04	0.44	−0.25	0.27	−0.60	0.10	−0.35	0.03	−0.02	−0.13	0.99	−0.11	1.00
(14)	$PatentsLQ_i^{local}$	−0.03	−0.02	−0.02	−0.05	0.03	−0.13	0.08	−0.07	0.16	0.21	−0.06	−0.10	−0.05
(15)	$PatentsLQ_i^{external}$	0.05	0.33	−0.10	0.08	−0.20	−0.20	−0.25	0.07	−0.11	−0.05	0.31	0.00	0.23
(16)	$Publications_i^{local}$	0.32	0.13	0.41	0.24	0.06	−0.08	0.43	0.26	0.39	0.66	−0.17	0.59	−0.16
(17)	$Publications_i^{external}$	0.09	0.49	−0.15	0.29	−0.48	0.01	−0.51	0.09	−0.16	−0.13	0.77	−0.10	0.77
(18)	$PublicationsHQ_i^{local}$	0.37	0.20	0.44	0.32	−0.01	−0.01	0.30	0.34	0.40	0.64	−0.11	0.71	−0.11
(19)	$PublicationsHQ_i^{external}$	0.09	0.44	−0.15	0.28	−0.48	0.04	−0.46	0.08	−0.14	−0.12	0.76	−0.10	0.77
(20)	$PublicationsLQ_i^{local}$	0.24	0.08	0.16	0.11	0.08	−0.07	0.20	0.29	0.21	0.39	−0.10	0.21	−0.10
(21)	$PublicationsLQ_i^{external}$	0.00	0.27	−0.05	0.13	−0.24	0.01	−0.37	0.09	−0.06	−0.09	0.48	−0.05	0.43
(22)	$Graduates_i^{local}$	0.31	0.08	0.41	0.20	0.11	−0.09	0.43	0.25	0.38	0.65	−0.19	0.57	−0.19
(23)	$Graduates_i^{external}$	0.05	0.43	−0.15	0.19	−0.39	−0.03	−0.54	0.10	−0.17	−0.17	0.76	−0.14	0.74
(24)	$GraduatesHQ_i^{local}$	0.36	0.19	0.43	0.31	0.01	−0.01	0.30	0.34	0.39	0.64	−0.13	0.71	−0.12
(25)	$GraduatesHQ_i^{external}$	0.05	0.38	−0.14	0.19	−0.41	0.02	−0.48	0.09	−0.16	−0.16	0.76	−0.14	0.77
(26)	$GraduatesLQ_i^{local}$	0.24	0.04	0.10	0.02	0.16	−0.11	0.24	0.27	0.15	0.30	−0.12	0.12	−0.12
(27)	$GraduatesLQ_i^{external}$	0.04	0.15	−0.01	0.01	−0.12	−0.07	−0.28	0.08	−0.04	−0.07	0.40	−0.04	0.35

Table 3 continued

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	
(1)														
(2)														
(3)														
(4)														
(5)														
(6)														
(7)														
(8)														
(9)														
(10)														
(11)														
(12)														
(13)														
(14)	1.00													
(15)	−0.14	1.00												
(16)	0.27	−0.11	1.00											
(17)	−0.11	0.31	−0.28	1.00										
(18)	−0.16	−0.04	0.81	−0.18	1.00									
(19)	−0.09	0.09	−0.24	0.95	−0.17	1.00								
(20)	0.61	−0.10	0.54	−0.20	0.07	−0.15	1.00							
(21)	−0.13	0.64	−0.21	0.54	−0.09	0.33	−0.20	1.00						
(22)	0.29	−0.12	0.99	−0.28	0.79	−0.25	0.54	−0.23	1.00					
(23)	−0.12	0.38	−0.30	0.97	−0.20	0.91	−0.20	0.57	−0.29	1.00				
(24)	−0.17	−0.04	0.81	−0.19	0.99	−0.18	0.06	−0.10	0.79	−0.21	1.00			
(25)	−0.08	0.10	−0.26	0.94	−0.19	0.98	−0.14	0.33	−0.25	0.93	−0.20	1.00		
(26)	0.56	−0.09	0.47	−0.19	−0.01	−0.14	0.91	−0.19	0.51	−0.17	−0.01	−0.12	1.00	
(27)	−0.11	0.71	−0.16	0.37	−0.06	0.15	−0.15	0.85	−0.15	0.48	−0.06	0.19	−0.13	1.00

All university variables are in logarithms

Table 4 Impact of local and external university knowledge, depending on the nature of the knowledge (Eq. 1)

	I Patents	II Publications	III Graduates
Incumbents/ Employees$_i$	0.031***	0.032***	0.033***
	(0.007)	(0.008)	(0.007)
KIFs/Incumbents$_i$	0.041	0.062**	0.063***
	(0.026)	(0.024)	(0.024)
VA/Employees$_i$	0.044**	0.044***	0.044***
	(0.018)	(0.016)	(0.016)
Unemployment$_i$	0.029	0.031	0.030
	(0.030)	(0.030)	(0.030)
Border$_i$	−0.438**	−0.534***	−0.544***
	(0.174)	(0.180)	(0.180)
Size$_i$	0.175***	0.181***	0.179***
	(0.037)	(0.044)	(0.045)
PopDensity$_i$	0.317	0.300	0.286
	(0.221)	(0.228)	(0.228)
BI$_i$	0.246*	0.323**	0.314**
	(0.134)	(0.134)	(0.135)
log x_i^{local}	0.246**	0.026	0.025
	(0.101)	(0.018)	(0.018)
log x_i^{external}	0.562**	0.091	0.080
	(0.241)	(0.065)	(0.070)
Constant	−3.075***	−3.403***	−3.458***
	(1.046)	(0.735)	(0.757)
NUTS 1 dummies	Yes	Yes	Yes
Number of observations	103	103	103
Log-likelihood	−394.144	−397.261	−397.534
LR test $\chi^2(1)$	5.957**	2.384	1.848

Negative binomial regression estimates of the impact of local and external university knowledge, depending on the nature of university knowledge: patents (column I), publications (column II), and graduates (column III). The dependent variable is the number of new KIFs in province *i*. Standard errors are in brackets

*,**, *** Significant at the 10, 5, 1 % level, respectively. The LR test refers to the null hypothesis that the coefficient of x_i^{external} equals zero (the LR statistic has a Chi-square distribution with one degree of freedom)

variable is the logarithm of the number of new KIFs in the province). The results are reasonably in line with those presented earlier.

Third, although the 2-year time lag between the number of new KIFs and the university variables lowers the risk of endogeneity due to reverse causality one may argue that unobserved factors affect both the number of new KIFs in a province and the scientific productivity of universities located in the same province or in surrounding provinces. Hence, the presence of an omitted variable bias might still affect our results. To address this issue, we run instrumental variable regressions for each type of knowledge considered. More specifically, we run two-stage least squares (2SLS) regressions in which the dependent variable is the logarithm of the number of new KIFs in the province. In considering the impact of university knowledge without distinguishing between high- and low-quality universities [with a specification that is similar to Eq. (1) in the negative binomial regression model] we used as instruments for the local university variables (i.e., Patents$_i^{\text{local}}$, Publications$_i^{\text{local}}$, and Graduates$_i^{\text{local}}$): (1) the presence of universities in the province, (2) the number of EU projects in which the universities in the province were lead partners in the period 2000–2006, and (3) the amount of funding received from the Italian Ministry of Education and Research to conduct research projects of national interest in the period 2001–2006. For the external university variables (i.e., Patents$_i^{\text{external}}$, Publications$_i^{\text{external}}$, and Graduates$_i^{\text{external}}$) we calculated the spatially weighted measures of the above-mentioned instrumental variables according to Eq. (2). We considered the same decay parameter values used for each type of university knowledge (i.e., 1.7, 4.6, and 4.4 for patents, publications, and graduates, respectively). With respect to the impact of high- and low-quality university knowledge [with a specification that is similar to Eq. (3) in the negative binomial regression model], we distinguished the same set of instruments according to the quality of university. With respect to the strength of our instruments, *F*-tests of the first-stage regression results always reject the null hypothesis that the above-mentioned instrumental variables are jointly equal to zero. Furthermore, the instruments are valid, as confirmed by Sargan tests, on the basis of which we do not reject the null hypothesis that the instruments are uncorrelated with the error terms in the second-stage regressions.

The results of these tests are available from the authors upon request. The results concerning the impact of local and external university knowledge as functions of the nature and quality of the knowledge are similar to those reported in Table 5.

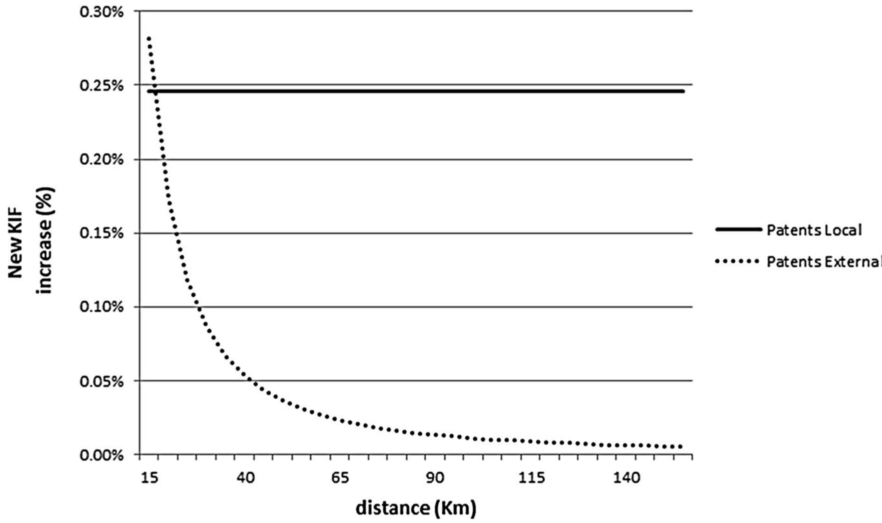

Fig. 2 Expected increase in the number of new KIFs in the focal province due to a 1 % increase in patents

6 Discussion and conclusions

Scholars agree that universities influence economic activities in their geographic areas (Ponds et al. 2011). Starting from this general premise, this paper presents empirical evidence of *how far in space* university knowledge contributes to local entrepreneurship. As university knowledge is deemed to be particularly important for firms operating in knowledge-intensive industries, we focused on the creation of new KIFs and considered two relevant dimensions of knowledge: its *nature* (tacit versus codified) and its *quality*.

In accordance with the literature (e.g., Woodward et al. 2006; Kirchhoff et al. 2007; Baptista and Mendonça 2010; Acosta et al. 2011), our results showed that *local university knowledge*, i.e., knowledge produced by universities located in a focal province, influences new KIF creation in that province. Moreover, academic patents influence the creation of new KIFs even at a distance from their producing universities. The effect of *external university knowledge* codified in academic patents on new KIF creation is positive and significant. Conversely, tacit knowledge embodied in university graduates and knowledge codified in publications do not cross the boundaries of the province. In other words, these two types of knowledge do not exert any significant effect on new KIF creation outside the province in which they are produced. These results apply to *high-quality universities*. Low-quality universities do not have any positive impact on new KIF creation, either locally or at greater distances, regardless of the type of knowledge under consideration.

The results of this study advance extant knowledge in several respects. First and foremost, by explicitly distinguishing between *local* and *external university knowledge* and computing distance decay parameters for each knowledge type, we bridged research analyzing the impact of university presence on local entrepreneurship (see Acosta et al. 2011 and Bonaccorsi et al. 2014 for recent surveys of this literature) with the literature on the role of proximity in the use of university knowledge in economic activities (Anselin et al. 2000a, b; Audretsch et al. 2012). In so doing, we filled an important research gap. While it has been shown that universities do matter for new firm creation at the local level, we still need to learn more about whether and how rapidly such an impact diminishes with distance. In particular, in comparison with previous studies that have explored this issue (e.g., Woodward et al. 2006), we considered different types of university knowledge and analyzed how far they go in space depending on their *tacit* or *codified nature* and their *quality*. Thus, we add to the research on the role of knowledge nature in shaping the impact of distance on the use of university knowledge (e.g., Arundel and Geuna 2004), by studying this issue with respect to new firm creation. In this regard, our findings are in line with the literature that has discussed the use of university knowledge in firms' innovation processes. It is not surprising that knowledge embodied in individuals, which has a tacit nature, generates *highly*

Table 5 Impact of local and external university knowledge, depending on the nature and quality of knowledge (Eq. 3)

	I Patents	II Publications	III Graduates
Incumbents/Employees$_i$	0.032***	0.031***	0.032***
	(0.008)	(0.008)	(0.007)
KIFs/Incumbents$_i$	0.045*	0.052*	0.052*
	(0.025)	(0.027)	(0.027)
VA/Employees$_i$	0.045***	0.046***	0.047***
	(0.017)	(0.016)	(0.016)
Unemployment$_i$	0.030	0.028	0.028
	(0.029)	(0.029)	(0.029)
Border$_i$	−0.447**	−0.558***	−0.540***
	(0.183)	(0.175)	(0.161)
Size$_i$	0.176***	0.188***	0.181***
	(0.038)	(0.044)	(0.047)
PopDensity$_i$	0.316	0.289	0.225
	(0.233)	(0.243)	(0.248)
BI$_i$	0.234*	0.326**	0.309**
	(0.129)	(0.131)	(0.129)
log $x\mathrm{HQ}_i^{\mathrm{local}}$	0.234**	0.030*	0.033*
	(0.097)	(0.015)	(0.017)
log $x\mathrm{HQ}_i^{\mathrm{external}}$	0.557**	0.064	0.066
	(0.234)	(0.057)	(0.058)
log $x\mathrm{LQ}_i^{\mathrm{local}}$	0.273	−0.004	0.006
	(0.210)	(0.020)	(0.021)
log $x\mathrm{LQ}_i^{\mathrm{external}}$	−0.070	0.100	0.091
	(0.942)	(0.063)	(0.061)
Constant	−3.135***	−3.351***	−3.419***
	(1.015)	(0.771)	(0.766)
NUTS 1 dummies	Yes	Yes	Yes
Number of observations	103	103	103
Log-likelihood	−394.066	−395.696	−395.659
LR test $\chi^2(2)$	2.137	2.395	2.562

Negative binomial regression estimates of the impact of local and external university knowledge, depending on the nature and quality of university knowledge: patents (column I), publications (column II), and graduates (column III). The dependent variable is the number of new KIFs in province *i*. Standard errors are in brackets

*, **, *** Significant at the 10, 5, 1 % level, respectively. The LR test refers to the null hypothesis that the coefficients of $x\mathrm{LQ}_i^{\mathrm{local}}$ and $x\mathrm{LQ}_i^{\mathrm{external}}$ are equal to zero (the LR statistic has a Chi-square distribution with two degrees of freedom)

localized spillovers that can be captured only by neighboring incumbents and prospective entrepreneurs. Conversely, distance might be expected to be neutral with respect to knowledge codified in scientific publications, which can be accessed from virtually everywhere. However, the codification of scientific knowledge in publications is conducted on the basis of a *specialized vocabulary* (Cowan et al. 2000) developed by the epistemic communities that form around scientific fields (Steinmueller 2000). Community members learn how to understand and communicate their scientific results in publications through prolonged studies and common experiences. The specialized vocabulary used in scientific publications can be disclosed to practitioners only through face-to-face interactions with scientists. These interactions are clearly favored by geographic proximity (Cohen et al. 2002; Morgan 2004; Storper and Venables 2004; Boschma 2005), which therefore is a sine qua non condition for publications to fully unleash their benefits for economic activities (Breschi and Lissoni 2001). Finally, the paper acknowledged the prominence of the quality of university knowledge, as mirrored by the quality of universities producing it, which is an issue that needs more scholarly attention. To the best of our knowledge, this is the first study to examine the role of quality in determining how far in space university knowledge contributes to local entrepreneurship. A closely related study in this respect is that of Laursen et al. (2011), who, however, focused on incumbent firms and evaluated the effect of the quality of universities on firms' decisions to collaborate with them.

Our study has some limitations that offer fertile ground for future research. First, we found that tacit knowledge embodied in university graduates and knowledge codified in scientific publications are highly localized. With respect to the former, we argued that individuals are scarcely mobile across space, while with respect to the latter, we referred to the importance of personal contacts with academic personnel. However, we observed *directly* neither individual mobility nor contacts between university researchers and would-be entrepreneurs. In light of the call for better understanding of microlevel factors in entrepreneurs' location choices (Arauzo-Carod et al. 2010), future research should analyze these aspects in depth, for instance, using fine-grained data obtained through case studies or surveys. In particular, the role of university graduates in new KIF creation can be assessed by studying how many new KIFs in a focal area are

Table 6 Impact of university knowledge codified in patents at different distance thresholds

	I 20 km	II 30 km	III 40 km	IV 50 km	V 60 km	VI 70 km
Incumbents/Employees$_i$	0.032***	0.031***	0.031***	0.030***	0.030***	0.030***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
KIFs/Incumbents$_i$	0.047*	0.046*	0.046*	0.035	0.036	0.035
	(0.025)	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)
VA/Employees$_i$	0.046***	0.046***	0.047***	0.040***	0.038**	0.038**
	(0.017)	(0.017)	(0.017)	(0.015)	(0.016)	(0.016)
Unemployment$_i$	0.031	0.034	0.033	0.020	0.025	0.024
	(0.028)	(0.028)	(0.030)	(0.029)	(0.031)	(0.029)
Border$_i$	−0.443**	−0.407**	−0.413**	−0.450**	−0.469**	−0.462**
	(0.180)	(0.168)	(0.175)	(0.192)	(0.195)	(0.193)
Size$_i$	0.178***	0.182***	0.181***	0.166***	0.168***	0.168***
	(0.038)	(0.038)	(0.038)	(0.036)	(0.039)	(0.037)
PopDensity$_i$	0.313	0.332	0.323	0.383*	0.366	0.370
	(0.237)	(0.233)	(0.225)	(0.229)	(0.243)	(0.233)
BI$_i$	0.234*	0.248*	0.232*	0.239*	0.238*	0.237*
	(0.128)	(0.131)	(0.130)	(0.139)	(0.142)	(0.132)
log PatentsHQ$_i^{<K}$	0.223**	0.223**	0.232**	0.293**	0.288***	0.302***
	(0.098)	(0.096)	(0.096)	(0.114)	(0.110)	(0.110)
log PatentsHQ$_i^{>K}$	0.603***	0.634***	0.682***	0.552**	0.397	0.476
	(0.231)	(0.214)	(0.207)	(0.266)	(0.292)	(0.489)
log PatentsLQ$_i^{<K}$	0.266	0.278	0.280	0.259	0.295	0.311
	(0.209)	(0.214)	(0.228)	(0.210)	(0.216)	(0.227)
log PatentsLQ$_i^{>K}$	−0.097	0.667	0.388	−1.518	−0.149	−0.895
	(0.929)	(0.991)	(1.589)	(1.559)	(1.946)	(3.305)
Constant	−3.259***	−3.323***	−3.324***	−2.535***	−2.518***	−2.484***
	(1.039)	(1.039)	(0.990)	(0.797)	(0.857)	(0.896)
NUTS 1 dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	103	103	103	103	103	103
Log likelihood	−393.961	−393.695	−393.418	−394.185	−394.415	−394.357

Negative binomial regression estimates of the impact of university knowledge codified in patents at different distance thresholds (20, 30, 40, 50, 60, and 70 km). The dependent variable is the number of new KIFs in province *i*. Standard errors are in brackets

*, **, *** Significant at the 10, 5, 1 % level, respectively

created by or employ graduates from local and distant universities. The importance of personal contacts for leveraging scientific publications can be assessed by interviewing nascent entrepreneurs on this point and asking them whether difficulties in establishing personal contacts have restrained them from using relevant scientific publications produced by distant universities.

Second, we considered only quality as a source of heterogeneity among universities, but universities usually differ in many other respects. Some universities have a proactive strategy toward their third mission and design mechanisms to support technology transfer (Fini et al. 2011; see below for a detailed discussion of these mechanisms) that influence how far university knowledge travels across space.

Third, we disregarded the possibility that the impact of university knowledge on local entrepreneurship may depend on institutional and social conditions that vary across territories. Previous studies have documented that differences exist across territories in the level of development of local financial markets, which, in turn, positively influences entry of new firms (Guiso et al. 2004). Better access to funds in more developed financial markets makes the costs of accessing high-quality university knowledge at long distances more affordable for prospective entrepreneurs. Therefore, an interesting extension of this research would consist of studying how the impact of external university knowledge on new KIF creation in a province varies depending on the local availability of bank loans, venture capital, and angel financing. Following a similar line of reasoning, some regional governments have launched programs to spur the creation of new ventures in knowledge-intensive industries through the provision of several support measures, including financial subsidies, training opportunities, and physical infrastructures in business incubators and science parks, to nascent entrepreneurs (Feldman 2001). To the extent that these programs enable prospective entrepreneurs to take advantage of knowledge generated by universities, they are likely to affect the spatial range of university knowledge.[22] Furthermore, *localized social capital* (Laursen et al. 2012) may also play a role. As we posit that the transfer of knowledge codified in publications is enabled by personal contacts, we should expect a stronger effect of this type of knowledge in provinces where high levels of localized social capital favor these contacts.

Finally, this is a cross-sectional study, with data on new KIF creation as of 2010. Although we controlled for a large number of province-specific factors and carefully addressed the issue of endogeneity, the availability of panel data would have strengthened our analysis. Indeed, it would have allowed us to investigate whether time-varying effects are at work. Specifically, new KIF creation in 2010 was negatively affected by the adverse macroeconomic conditions forged by the current global crisis. Hence, it would be interesting to replicate this study in boom periods to assess whether macroeconomic conditions influence the spatial range of university knowledge.

Despite the aforementioned limitations, our findings offer some interesting insights for policymakers and university officers. First and foremost, they indicate that a high-quality university system is the sine qua non condition for university knowledge to have a positive impact on knowledge-intensive entrepreneurship. Low-quality universities do not promote new KIF creation, either locally or at long distances. In addition, because only technological knowledge codified in academic patents crosses provincial borders and its positive impact on entrepreneurship rapidly diminishes with distance, high-quality universities are only of partial help in stimulating entrepreneurship in peripheral areas. Accordingly, national and regional governments seeking to increase the entrepreneurial impact of university systems face a crucial dilemma. To foster entrepreneurship and regional economic growth in peripheral areas, they might want to establish high-quality universities in those areas. However, this is a resource-consuming undertaking, with uncertain and long-term returns. An alternative is to design appropriate policy schemes targeting existing universities, in close collaboration with university officers. Two areas of intervention seem especially promising. For a start, there is evidence that university researchers patent out of diverse motives, ranging from the need to protect their inventions for future commercialization to the signaling of specific research competences (Bodas Freitas and Nuvolari 2012). Support from technology transfer offices (TTOs) and individual incentives can play crucial roles in promoting successful academic patenting (e.g., Dasgupta and David 1994). TTOs can help scientists conduct the complex patent filing process and identify commercial opportunities for their inventions (e.g., Thursby and Thursby 2002; Siegel et al. 2003; Geuna and Nesta 2006). In addition, specific incentives, such as introducing leaves of absence for patent development, freezing the tenure clock for academic personnel who are willing to pursue research toward commercialization, granting appropriate recognition to patents in individual evaluation and compensation schemes, and simply offering financial support for patenting activities, can be implemented by

[22] For illustrative purposes, let us consider a dedicated training program taught by professors of a high-quality but distant university or a large incubator located on the premises of a local university. In the former case, entrepreneurship in the focal area is likely to be positively influenced by the knowledge produced by the distant university, while in the latter case, the knowledge produced by the local university is likely to remain highly localized.

policymakers and university officers. Prior research has shown that these individual-level mechanisms. Affect the number of patents that faculty members produce (Huang et al. 2011). Furthermore, policymakers and university officers should discuss how to foster the mobility of university graduates and personal contacts between academic personnel and practitioners, with the aim of making the tacit knowledge embodied in university graduates and the knowledge codified in scientific publications cross provincial borders; For instance, in Italy as in many other countries, students often leave their provinces of birth to attend high-quality universities. Hence, support schemes for returnees who want to start businesses in their home provinces may be very helpful. Likewise, effective bridges between academics and practitioners should be established. Organizing workshops and focus groups with the aim of making academics aware of the technological needs of practitioners would be valuable and might even have an indirect positive effect: it has been shown that interactions with industry can steer academics toward patenting (Agrawal and Henderson 2002). However, policymakers and university officers should be aware that practitioners are sometimes uncomfortable with academic values and attitudes, such as orientation toward path-breaking discoveries, early publication of research results, and considering knowledge as a public good (Siegel et al. 2004). Overcoming such cultural gaps, by appropriately mobilizing directors of TTOs or university incubators, for instance, may be crucial to fostering fruitful communication between the academe and the productive system.

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Appendix 1: Estimation of the decay parameter

To set the distance decay parameter α for each type of university knowledge (patents, publications, and graduates), we evaluated the value that maximizes the log-likelihood function of the econometric model described by Eq. (3).[23] We tested increasing values of α from 0 to 5 in increments of 0.1.

For each type of university knowledge, Fig. 3 shows the likelihood ratio LR = −2[log-likelihood(unrestricted model) − log-likelihood(restricted model)], where the unrestricted model corresponds to Eq. (3), while in the restricted model, we set to zero the coefficients of external university knowledge variables (i.e., $x\text{HQ}_i^{\text{external}}$ and $x\text{LQ}_i^{\text{external}}$). More specifically, depending on the value of the decay parameter α considered, the dotted, grey, and dashed lines represent the LR values associated with patents, publications, and graduates, respectively. Finally, the bold line is the critical value of the Chi-square distribution with two degrees of freedom in an LR test at 95 % confidence level (if the LR is higher than this critical value, we reject, with 95 % confidence, the null hypothesis that external university knowledge variables are zero).

Figure 3 shows that the values that maximize the log-likelihood (i.e., the LR) are 1.7, 4.6, and 4.4 for patents, publications, and graduates, respectively. Accordingly, these values are used as the decay parameters in evaluating the effect of external university knowledge on new KIF creation. Finally, when considering these maximum values, it is worth noting that we can reject the null hypothesis that external university knowledge variables are zero only for patents (at the 5 % significance level).

Appendix 2: Industry classification

See Table 7.

Appendix 3: Publications

For each university, we computed a measure that accounts for the differences in the frequency of publication in each of the 151 research areas listed in the ISI Web of Science. Specifically, for each university u and ISI research area a, we first computed the ratio of the number of ISI publications of university u in research area a to the total number of ISI publications generated by the 80 Italian universities in research area a:

[23] Results concerning Eq. (1) are similar to those reported here. They are not shown for the sake of synthesis, but are available from the authors upon request.

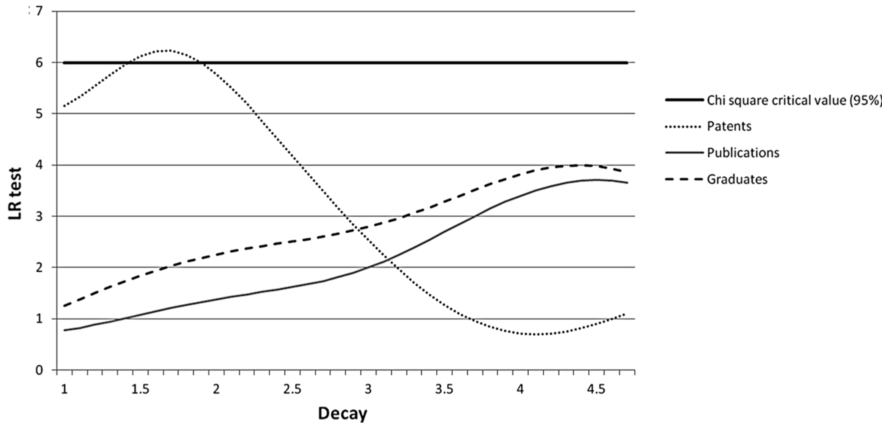

Fig. 3 Likelihood ratio tests of external university variables (patents, publications, and graduates), depending on the decay parameter

Table 7 Knowledge-intensive industries

NACE code	Industry description	Number of new KIFs	Percentage out of the total
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	3	0.06
C26	Manufacture of computer, electronic, and optical products	112	2.35
J62	Computer programming, consultancy, and related activities	750	15.75
J63	Information service activities	492	10.33
M69	Legal and accounting activities	114	2.39
M70	Activities of head offices; management consultancy activities	1,263	26.53
M71	Architectural and engineering activities; technical testing and analysis	522	10.96
M72	Scientific research and development	92	1.93
M73	Advertising and market research	393	8.25
M74	Other professional, scientific, and technical activities	889	18.67
R90	Creative, arts, and entertainment activities	127	2.67
R91	Libraries, archives, museums, and other cultural activities	4	0.08
	Total	4,761	100.00

$$S_{u,a} = \frac{\text{ISI Publications}_{u,a}}{\sum_{u=1}^{80} \text{ISI Publications}_{u,a}}.$$

The ratio $S_{u,a}$ represents the proportion of ISI publications in research area a of each university u with respect to the total number of ISI publications generated by all Italian universities in research area a.

Then, for each university u, we calculated the arithmetic mean of the ratios $S_{u,a}$ across the 151 research areas:

$$\text{AS}_u = \frac{1}{151}\sum_{u=1}^{151} S_{u,a}.$$

For each university u, AS_u represents the average proportion of ISI publications across research areas. Finally, to obtain a count measure, we multiplied AS_u by the total number of ISI publications generated by all Italian universities in the period 2000–2008 (339,737):

$$\text{Publications}_u^* = 339,737 \cdot \text{AS}_u.$$

In other words, we used the average proportion of ISI publications produced by each university u across research areas (AS_u) to attribute to each university u the corresponding fraction of the total number of ISI publications generated by all Italian universities.

Appendix 4: Robustness checks

See Tables 8 and 9.

Table 8 Impact of local and external university knowledge, depending on the nature and quality of knowledge, controlling for other agglomeration effects

	I Patents	II Publications	III Graduates
Incumbents/Employees$_i$	0.033***	0.032***	0.033***
	(0.008)	(0.008)	(0.007)
KIFs/Incumbents$_i$	0.044*	0.050*	0.050*
	(0.025)	(0.027)	(0.027)
VA/Employees$_i$	0.044**	0.046***	0.046***
	(0.017)	(0.016)	(0.016)
Unemployment$_i$	0.025	0.024	0.024
	(0.028)	(0.029)	(0.028)
Border$_i$	−0.443**	−0.558***	−0.540***
	(0.177)	(0.173)	(0.159)
Size$_i$	0.181***	0.191***	0.186***
	(0.037)	(0.044)	(0.047)
PopDensity$_i$	0.302	0.282	0.222
	(0.245)	(0.247)	(0.247)
BI$_i$	0.231*	0.325**	0.309**
	(0.129)	(0.133)	(0.131)
log $x\mathrm{HQ}_i^{\mathrm{local}}$	0.229**	0.030*	0.033*
	(0.096)	(0.015)	(0.017)
log $x\mathrm{HQ}_i^{\mathrm{external}}$	0.608**	0.068	0.074
	(0.247)	(0.059)	(0.059)
log $x\mathrm{LQ}_i^{\mathrm{local}}$	0.262	−0.005	0.004
	(0.206)	(0.020)	(0.022)
log $x\mathrm{LQ}_i^{\mathrm{external}}$	−0.059	0.097	0.090
	(0.907)	(0.063)	(0.060)
Incumbents/Employees$_i^{200}$	−0.008	−0.006	−0.007
	(0.015)	(0.015)	(0.016)
Constant	−2.826***	−3.066***	−3.092***
	(1.008)	(0.852)	(0.867)
NUTS 1 dummies	Yes	Yes	Yes
Number of observations	103	103	103
Log-likelihood	−394.066	−395.696	−395.659
LR test $\chi^2(2)$	1.972	2.348	2.461

Negative binomial regression estimates of the impact of local and external university knowledge, depending on the nature and quality of university knowledge: patents (column I), publications (column II), and graduates (column III). The dependent variable is the number of new KIFs in province *i*. Standard errors are in brackets

*, **, *** Significant at the 10, 5, 1 % level, respectively. The LR test refers to the null hypothesis that the coefficients of $x\mathrm{LQ}_i^{\mathrm{local}}$ and $x\mathrm{LQ}_i^{\mathrm{external}}$ are jointly equal to zero (the LR statistic has a Chi-square distribution with two degrees of freedom)

Table 9 The spatial range of university knowledge, depending on the nature and quality of knowledge—OLS and 2SLS regressions

	I Patents OLS	II Patents 2SLS	III Pub. OLS	IV Pub. 2SLS	V Graduates OLS	VI Graduates 2SLS
Incumbents/Employees$_i$	0.037***	0.038***	0.036***	0.038***	0.036***	0.038***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
KIFs/Incumbents$_i$	0.038	0.049	0.047	0.054	0.047	0.052
	(0.033)	(0.032)	(0.031)	(0.034)	(0.030)	(0.034)
VA/Employees$_i$	0.043*	0.047**	0.045*	0.042**	0.046**	0.043**
	(0.023)	(0.019)	(0.022)	(0.019)	(0.022)	(0.019)
Unemployment$_i$	0.016	0.015	0.014	0.011	0.014	0.011
	(0.035)	(0.029)	(0.036)	(0.030)	(0.036)	(0.031)
Border$_i$	−0.495**	−0.530***	−0.589***	−0.627***	−0.573***	−0.601***
	(0.200)	(0.182)	(0.184)	(0.156)	(0.170)	(0.152)
Size$_i$	0.168***	0.181***	0.182***	0.160***	0.176***	0.157***
	(0.043)	(0.040)	(0.048)	(0.045)	(0.050)	(0.047)
PopDensity$_i$	0.307	0.294	0.285	0.253	0.240	0.208
	(0.263)	(0.250)	(0.266)	(0.301)	(0.270)	(0.299)
BI$_i$	0.225	0.289**	0.275*	0.241*	0.268*	0.241*
	(0.145)	(0.135)	(0.139)	(0.140)	(0.138)	(0.134)
log $x\mathrm{HQ}_i^{\mathrm{local}}$	0.261**	0.163*	0.039*	0.037**	0.041*	0.041**
	(0.118)	(0.095)	(0.019)	(0.019)	(0.021)	(0.020)
log $x\mathrm{HQ}_i^{\mathrm{external}}$	0.512*	0.459*	0.064	−0.005	0.069	0.011
	(0.286)	(0.258)	(0.059)	(0.063)	(0.059)	(0.061)
log $x\mathrm{LQ}_i^{\mathrm{local}}$	0.358	−0.069	0.001	−0.000	0.008	0.012
	(0.241)	(0.319)	(0.026)	(0.025)	(0.027)	(0.026)
log $x\mathrm{LQ}_i^{\mathrm{external}}$	−0.704	−0.315	0.076	0.024	0.068	0.055
	(1.262)	(1.354)	(0.082)	(0.092)	(0.076)	(0.076)
Constant	−3.092**	−3.470***	−3.305***	−3.110***	−3.387***	−3.151***
	(1.202)	(1.102)	(1.067)	(0.969)	(1.082)	(0.972)
NUTS 1 dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	103	103	103	103	103	103
R^2	0.794	0.784	0.785	0.780	0.785	0.783
F (2) test	1.634		0.435		0.422	
χ^2(2) test		0.002		0.485		1.215

OLS and 2SLS estimates of the impact of local and external university knowledge, depending on the nature and quality of university knowledge: patents (column I), publications (column II), and graduates (column III). The dependent variable is the logarithm of the number of new KIFs in province i. Standard errors are in brackets

*, **, *** Significant at the 10, 5, 1 % level, respectively. The F test and the Chi-square test (two degrees of freedom) refer to the null hypothesis that the coefficients of $x\mathrm{LQ}_i^{\mathrm{local}}$ and $x\mathrm{LQ}_i^{\mathrm{external}}$ are jointly equal to zero

References

Abramovsky, L., Harrison, R., & Simpson, H. (2007). University research and the location of business R&D. *Economic Journal, 117*(519), 114–141.

Acosta, M., Coronado, D., & Flores, E. (2011). University spillovers and new business location in high-technology sectors: Spanish evidence. *Small Business Economics, 36*(3), 365–376.

Acs, Z., & Plummer, L. A. (2005). Penetrating the 'knowledge filter' in regional economies. *Annals of Regional Science, 39*(3), 439–456.

Addario, S., & Vuri, D. (2010). Entrepreneurship and market size. The case of young college graduates in Italy. *Labour Economics, 17*(5), 848–858.

Agrawal, A., & Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. *Management Science, 48*(1), 44–60.

Alvesson, M. (1995). *Management of knowledge-intensive companies*. Berlin, GE: Walter de Gruyter.
Anselin, L., Varga, A., & Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics, 42*(3), 422–448.
Anselin, L., Varga, A., & Acs, Z. (2000a). Geographical spillovers and university research: A spatial econometric perspective. *Growth and Change, 31*(4), 501–515.
Anselin, L., Varga, A., & Acs, Z. (2000b). Geographic and sectoral characteristics of academic knowledge externalities. *Papers in Regional Science, 79*(4), 435–443.
Arauzo-Carod, J. M., Liviano-Solis, D., & Manjon-Antolin, M. (2010). Empirical studies in industrial location: An assessment of their methods and results. *Journal of Regional Science, 50*(3), 685–711.
Armington, C., & Acs, Z. (2002). The determinants of regional variation in new firm formation. *Regional Studies, 36*(1), 33–45.
Arundel, A., & Geuna, A. (2004). Proximity and the use of public science by innovative European firms. *Economics of Innovation and New Technologies, 13*(6), 559–580.
Astebro, T. B., Bazzazian, N., & Braguinsky, S. (2012). Startups by recent university graduates and their faculty: Implications for university entrepreneurship policy. *Research Policy, 41*(4), 663–677.
Audretsch, D. B., Hulsbeck, M., & Lehmann, E. E. (2012). Regional competitiveness, university spillovers, and entrepreneurial activity. *Small Business Economics, 39*(3), 587–601.
Audretsch, D. B., & Keilbach, M. (2004). Entrepreneurship capital and economic performance. *Regional Studies, 38*(8), 949–959.
Audretsch, D. B., & Keilbach, M. (2005). Entrepreneurship capital and regional growth. *Annals of Regional Science, 39*(3), 457–469.
Audretsch, D. B., & Keilbach, M. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*(7), 1242–1254.
Audretsch, D. B., & Keilbach, M. (2008). Resolving the knowledge paradox: Knowledge-spillover entrepreneurship and economic growth. *Research Policy, 37*(10), 1697–1705.
Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy, 34*(8), 1191–1202.
Audretsch, D. B., Lehmann, E. E., & Warning, S. (2005). University spillovers and new firm location. *Research Policy, 34*(7), 1113–1122.
Baltzopoulos, A., & Broström, A. (2013). Attractors of entrepreneurial activity: Universities, regions and alumni entrepreneurs. *Regional Studies, 47*(6), 934–949.
Baptista, R., & Mendonça, J. (2010). Proximity to knowledge sources and the location of knowledge-based start-ups. *Annals of Regional Science, 45*(1), 5–29.
Baptista, R., & Swann, P. (1999). A comparison of clustering dynamics in the US and UK computer industries. *Journal of Evolutionary Economics, 9*(3), 373–399.
Belenzon, S., & Schankerman, A. (2013). Spreading the word: Geography, policy and knowledge spillovers. *Review of Economics and Statistics,* 95(3), 884–890.
Bodas Freitas, I., & Nuvolari, A. (2012). Traditional versus heterodox motives for academic patenting: Evidence from the Netherlands. *Industry and Innovation, 19*(8), 671–695.
Bonaccorsi, A., Colombo, M. G., Guerini, M., & Rossi-Lamastra, C. (2014). How universities contribute to the creation of knowledge intensive firms: Detailed evidence on the Italian case. In A. Bonaccorsi (Ed.), *Knowledge, diversity and performance in European higher education: A changing landscape* (pp. 205–229). Cheltenham, UK: Edward Elgar.
Bonaccorsi, A., Lepori, B., Brandt, T., De Filippo, D., Niederl, A., Schmoch, U., et al. (2012). Mapping the European higher education landscape. New Empirical Insights from the EUMIDA Project. Working paper. http://www.cwts.nl/pdf/BookofAbstracts2010_version_15072010.pdf#page=164. Accessed 12 Mar 2012.
Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39*(1), 61–74.
Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review, 47*(4), 687–710.
Breschi, S., & Lissoni, F. (2001). Knowledge spillovers and local innovation systems: A critical survey. *Industrial and Corporate Change, 10*(4), 975–1005.
Buenstorf, G., & Klepper, S. (2009). Heritage and agglomeration: The Akron tyre cluster revisited. *Economic Journal, 119*(537), 705–733.
Cameron, C., & Trivedi, P. (1990). Regression based tests for overdispersion in the Poisson model. *Journal of Econometrics, 46*(3), 347–364.
Carree, M. A., Della Malva, A., & Santarelli, E. (2012, forthcoming). The contribution of universities to growth: Empirical evidence for Italy. *Journal of Technology Transfer*. doi:10.1007/s10961-012-9282-7.
Carree, M. A., Santarelli, E., & Verheul, I. (2008). Firm entry and exit in Italian provinces and the relationship with unemployment. *International Entrepreneurship & Management Journal, 4*(2), 171–186.
Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.
Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2002). Links and impacts: The influence of public research on industrial R&D. *Management Science, 48*(1), 1–23.
Colombo, M. G., & Delmastro, M. (2002). How effective are technology incubators? Evidence from Italy. *Research Policy, 31*(7), 1103–1122.
Colombo, M. G., & Piva, E. (2012). Firms' genetic characteristics and competence-enlarging strategies: A comparison of academic and non-academic high-tech start-ups. *Research Policy, 41*(1), 79–92.
Cowan, R., David, P. A., & Foray, D. (2000). The explicit economics of knowledge codification and tacitness. *Industrial and Corporate Change, 9*(2), 211–254.
Dahl, M. S., & Sorenson, O. (2009). The embedded entrepreneur. *European Management Review, 6*(3), 172–181.
Dasgupta, P., & David, P. A. (1994). Towards a new economic of science. *Research Policy, 23*(5), 487–521.
Döring, T., & Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth? A survey of the literature. *Regional Studies, 40*(3), 375–395.

Drucker, J., & Goldstein, H. (2007). Assessing the regional economic development impacts of universities: A review of current approaches. *International Regional Science Review, 30*(1), 20–46.

European Commission. (2010). Feasibility study for creating a European University Data Collection [Contract No. RTD/C/C4/2009/0233402]. Technical report. http://ec.europa.eu/research/era/docs/en/eumida-final-report.pdf. Accessed 6 Feb 2012.

Feldman, M. (2001). The entrepreneurial event revisited: Firm formation in a regional context. *Industrial and Corporate Change, 10*(4), 861–881.

Figueiredo, O., Guimaraes, P., & Woodward, D. P. (2002). Home-field advantage: Location decisions of Portuguese entrepreneurs. *Journal of Urban Economics, 52*(2), 341–361.

Fini, R., Grimaldi, R., Santoni, S., & Sobrero, S. (2011). Complements or substitutes? The role of universities and local context in supporting the creation of academic spin-offs. *Research Policy, 40*(8), 1113–1127.

Fleming, L., & Sorenson, O. (2004). Science as a map in technological search. *Strategic Management Journal, 25*(8–9), 909–928.

Geuna, A., & Nesta, L. J. J. (2006). University patenting and its effects on academic research: The emerging European evidence. *Research Policy, 35*(6), 790–807.

Glänzel, W. (2000). Science in Scandinavia: A bibliometric approach. *Scientometrics, 48*(2), 121–150.

Greene, W. H. (2003). *Econometric analysis*. Upper Saddle River, NJ: Prentice Hall.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics, 10*(1), 92–116.

Guiso, L., Sapienza, P., & Zingales, L. (2004). Does local financial development matter? *Quarterly Journal of Economics, 119*(3), 929–969.

Harhoff, D. (1999). Firm formation and regional spillovers: Evidence from Germany. *Economics of Innovation and New Technology, 8*(1–2), 27–55.

Hoare, A., & Corver, M. (2010). The regional geography of new young graduate labour in the UK. *Regional Studies, 44*(4), 477–494.

Huang, C., Notten, A., & Rasters, N. (2011). Nanoscience and technology publications and patents: A review of social science studies and search strategies. *Journal of Technology Transfer, 36*(2), 145–172.

Huffman, D., & Quigley, J. M. (2002). The role of the university in attracting high tech entrepreneurship: A Silicon Valley tale. *Annals of Regional Science, 36*(4), 403–419.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics, 63*(3), 577–598.

Kirchhoff, B. A., Newbert, S. L., Hasan, I., & Armington, C. (2007). The influence of university R&D expenditures on new business formations and employment growth. *Entrepreneurship: Theory and Practice, 31*(4), 543–559.

Laursen, K., Masciarelli, F., & Prencipe, A. (2012). Regions matter: How localized social capital affects innovation and external knowledge acquisition. *Organization Science, 23*(1), 177–193.

Laursen, K., Reichstein, T., & Salter, A. (2011). Exploring the effect of geographical proximity and university quality on university–industry collaboration in the United Kingdom. *Regional Studies, 45*(4), 507–523.

Michelacci, C., & Silva, O. (2007). Why so many local entrepreneurs? *Review of Economics and Statistics, 89*(4), 615–633.

Morgan, K. (2004). The exaggerated death of geography: Learning, proximity and territorial innovation systems. *Journal of Economic Geography, 4*(1), 3–21.

Mueller, P. (2006). Exploring the knowledge filter: How entrepreneurship and university–industry relationships drive economic growth. *Research Policy, 35*(10), 1499–1508.

NETVAL. (2012). IX Rapporto Netval sulla Valorizzazione della Ricerca Pubblica Italiana. http://www.netval.it/contenuti/file/RapportoNETVAL_2012.pdf. Accessed 10 Dec 2012.

Parwada, J. T. (2008). The genesis of home bias? The location and portfolio choices of investment company start-ups. *Journal of Financial and Quantitative Analysis, 43*(1), 245–266.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., et al. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy, 42*(2), 423–442.

Piergiovanni, R., Carree, M. A., & Santarelli, E. (2012). Creative industries, new business formation, and regional economic growth. *Small Business Economics, 39*(3), 539–560.

Piva, E., Grilli, L., & Rossi-Lamastra, C. (2011). The creation of high-tech entrepreneurial ventures at the local level: The role of local competences and communication infrastructures. *Industry & Innovation, 18*(6), 563–580.

Ponds, R., van Oort, F., & Frenken, K. (2011). Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. *Journal of Economic Geography, 10*(2), 231–255.

Rothaermel, F., Shanti, D. A., & Lin, J. (2007). University entrepreneurship: A taxonomy of the literature. *Industrial and Corporate Change, 16*(4), 691–791.

Scimago (2010). SIR World Report 2010—Global Ranking. Report Number: 2010-002. http://www.scimagoir.com/pdf/sir_2010_world_report_002.pdf. Accessed 20 Feb 2012.

Siegel, D., Waldman, D. A., Atwater, L. E., & Link, A. N. (2004). Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: Qualitative evidence from the commercialization of university technologies. *Journal of Engineering and Technology Management, 21*(1–2), 115–142.

Siegel, D., Waldman, D. A., & Link, A. N. (2003). Assessing the impact of organizational practices on the productivity of university technology transfer offices: An exploratory study. *Research Policy, 32*(1), 27–48.

Song, M., Berends, H., van der Bij, H., & Weggeman, M. (2007). The effect of IT and co-location on knowledge dissemination. *Journal of Product Innovation Management, 24*(1), 52–68.

Sorenson, O., & Audia, P. G. (2000). The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States. *American Journal of Sociology, 106*(2), 424–462.

Stam, E. (2007). Why butterflies don't leave. Locational behavior of entrepreneurial firms. *Economic Geography, 83*(1), 27–50.

Steinmueller, W. E. (2000). Will new information and communication technologies improve the 'codification' of knowledge? *Industrial and Corporate Changes, 9*(2), 361–376.

Stephan, P. E. (2012). *How economics shapes science*. Cambridge, MA: Harvard University Press.

Storper, M., & Venables, A. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography, 4*(4), 351–370.

Thursby, J. G., & Thursby, M. C. (2002). Who is selling the ivory tower? Sources of growth in university licensing. *Management Science, 48*(1), 90–104.

Varga, A. (2000). Local academic knowledge spillovers and the concentration of economic activity. *Journal of Regional Science, 40*(2), 289–309.

Woodward, D., Figueiredo, O., & Guimaraes, P. (2006). Beyond the Silicon Valley: University R&D and high technology location. *Journal of Urban Economics, 60*(1), 15–32.