The "first match" between high-tech entrepreneurial ventures and universities: the role of founders' social ties

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Abstract

This paper studies the collaborations between entrepreneurial ventures and universities by investigating the *"first match"*, namely, the probability that a given entrepreneurial venture, which has never established university collaborations before, forms a collaboration with a given university (out of all the possible collaborations it might have formed). Expanding on the literature about university–industry collaborations, we argue that the formation of the first match is socially bounded. Specifically, we contend that individual social ties, which the founders of an entrepreneurial venture have formed with the personnel of a given university as they worked there, increase the probability of a first match because these ties reduce the costs and increase the benefits of forming a collaboration (H1). We also hypothesize that geographical (H2) and cognitive proximity (H3) between entrepreneurial ventures and universities influence these costs and benefits, thus moderating the relation sub H1. Econometric estimations on a large set of dyads, which represent realized and potential first matches between Italian high-tech entrepreneurial ventures and universities, support our hypotheses.

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1 Introduction

During the last two decades, firms have shown an increasing propensity to collaborate with universities for accessing novel scientific and technological knowledge (e.g., Almeida et al. 2011; Bonaccorsi et al. 2014). The phenomenon has spurred massive scholarly attention and many works have studied the antecedents and the consequences—for instance on firm performance—of university–industry collaborations (see Ankrah and Al Tabbaa 2015 and Skute et al. 2019 for recent reviews of this literature). To date, this research stream has largely focused on collaborations between universities and established firms and has, instead, overlooked collaborations between universities and *entrepreneurial ventures*, i.e. young, independent firms established by one or more individuals with the aim of commercially exploiting a novel business idea (Hart 2003). Studies of collaborations between academic spin-offs[1] and their parents universities are a notable exception (Djokovic and Souitaris 2008; Miranda et al. 2018). However, academic spin-offs are just a minority of the whole entrepreneurial ventures and we still need to learn more on collaborations between universities and ventures, which do not necessarily have such a strong and direct linkage with the university context. The few studies, which have taken a step in this direction, explore the role of entrepreneurs' educational background in explaining the propensity of entrepreneurial ventures to engage in research collaborations with universities (Okamuro et al. 2011), the benefits—in terms of innovation output (George et al. 2002), productivity (Motohashi 2005), and employment growth (Toole et al. 2015)—for entrepreneurial ventures of collaborating with universities, and the motives and practices of these collaborations (van Stijn et al. 2018).

Conversely, to the best of our knowledge, no prior study has focused on what we call the *"first match"*, namely, the fact that a given entrepreneurial venture, which has never established university collaborations before, forms its first collaboration with a given university out of all the possible collaborations it might have formed. This is a relevant literature gap. Collaborations with universities can bring large benefits to entrepreneurial ventures, especially to those operating in high-tech industries (e.g., George et al. 2002; Motohashi 2005; Soh and Subramanian 2014). As entrepreneurial ventures are a major engine of innovation, new job creation, and, ultimately, economic growth (Criscuolo et al. 2014; Decker et al. 2014), entrepreneurial venture-university collaborations can positively impact the whole economic system. However, forming university collaborations is challenging for entrepreneurial ventures, even more so if this happens for the first time. As we discuss in Sect. 2, the information opacity and the lack of resources, which characterize these firms (van Stijn et al. 2018), make them unattractive partners for universities. More importantly to the aims of this study, entrepreneurial ventures must wisely select the universities with which forming their first matches. For a start, forming these matches requires to make (costly) relation-specific investments: resource-constrained entrepreneurial ventures must carefully choose to which university collaborations allocate their scant resources. Moreover, evidence exists that founders' initial decisions about the strategies and organization of their ventures become *imprinted* at the firm-level and drive their subsequent decisions (Mathias et al. 2015); accordingly, first matches constrain the opportunities of future collaborations.

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[1] Academic spinoffs are entrepreneurial ventures established with the aim of putting into practice the knowledge generated through the research activity of academic personnel (Miranda et al. 2018).

Taking inspiration from the ample research tradition, which stresses the importance of individuals' social ties for economic outcomes (see the seminal contributions of Blau 1977 and Granovetter 2005), this paper advances knowledge on what determines the first match between a given entrepreneurial venture and a given university by focusing attention on the *individual social ties* that entrepreneurial ventures' founders have established before incorporating their firms. Specifically, we hypothesize (H1) that the probability that a given entrepreneurial venture forms a first match with a given university (out of all the possible matches it might have formed) increase if the venture's founders worked as professors or researchers in that university, thus developing individual social ties within it.

Then, we analyze factors, which *weaken* the alleged positive relation sub H1, thus loosening the entrepreneurial ventures' tendency to form socially bounded collaborations. Analyzing these factors is of interest also in the light of the aforementioned imprinting phenomenon. If founders' individual social ties shape the probability of forming the first match, and, in turn, the first match influences the subsequent matches, founders' individual social ties, ultimately, constraints the ventures' possibilities of forming potentially beneficial collaborations with other universities in the future. Therefore, understanding what weakens the relation between individual social ties and the probability of forming the first match may help entrepreneurial ventures and policy makers to design strategies and policy schemes for overcoming these constraints.

In searching for the aforementioned factors, we take inspiration from research stating that *proximity* does matter for the formation of inter-organizational collaborations (Boschma 2005; Knoben and Oerlemans 2006). More specifically, as we explain in the Sect. 2, two dimensions of proximity are highly relevant for our investigation: *geographical proximity* (i.e., the spatial distance between two organizations) and *cognitive proximity* (i.e., the level of similarity between their knowledge bases). Accordingly, we put forth two additional research hypotheses. We argue that geographical proximity between an entrepreneurial venture and a university weakens the positive relation between the presence of founders' individual social ties and the probability that this entrepreneurial venture forms a first match with that university (H2). We also contend that the same hold true for cognitive proximity (H3).

In the empirical part of the paper, we apply a two-stage Heckman procedure (Heckman 1979) on a dataset of 295 Italian high-tech entrepreneurial ventures: 70 ventures have formed one (or more) first matches with Italian universities in the period 2004–2008, while 225 ventures (i.e., 295-70) have not formed any match with those universities. As described in Sect. 4, after controlling for possible selection biases through the first stage of the Heckman procedure, we perform its second stage, which constitutes our main econometric specification. This second stage runs on 5600 (70×80) university-venture dyads, which result from the combinations of the 70 collaborating entrepreneurial ventures and the 80 Italian universities with which these 70 entrepreneurial ventures might have potentially matched. In other words, these 5,600 dyads represent all the potential and realized entrepreneurial venture-university first matches.

Findings document that founders' individual social ties play a crucial role in the formation of the first matches. Specifically, the predicted probability of the first match is negligible if a venture's founders have no individual ties within the focal university. This probability is sizable if such ties exist, but it reduces as geographical proximity increases. A similar pattern emerges when considering cognitive proximity. These results are robust after controlling for a variety of potential confounding factors and when using different econometric specifications (see Sect. 5.2 for further details).

The paper proceeds as follows. In Sect. 2, we illustrate the conceptual background of the paper and put forth the research hypotheses. Section 3 describes the data. Section 4 presents the methodology of the econometric analysis, and the variables we use in econometric models. Section 5 discusses the results. Section 6 concludes the paper by highlighting its contributions to the literature, illustrating its limitations, indicating directions for future research, and sketching policy implications.

2 Conceptual background and research hypotheses

2.1 The benefits and costs of the first matches between entrepreneurial ventures and universities

A first match between an entrepreneurial venture and a university occurs if the benefits, which both parties obtain from this collaboration, outweigh their costs. Entrepreneurial ventures reap sizable benefits from university collaborations. Due to their young age and limited size, these firms have an immature organizational structure (Colombo et al. 2012a), scant production equipment, few (or even no) employees, and limited product backlogs (Colombo et al. 2016). Consequently, they enjoy much flexibility and can easily capture the business opportunities arising from university knowledge (on this theme, see also contributions in the Knowledge Spillover Theory of Entrepreneurship, e.g., Acs et al. 2013; Acs and Plummer 2005; Ghio et al. 2015). Furthermore, by collaborating with universities, entrepreneurial ventures can solve technical problems, which their resource-constraints impede to manage internally (e.g., Cohen et al. 2002). The benefits of university collaborations for entrepreneurial ventures also include gains in terms of social capital and reputation (van Stijn et al. 2018). Through university collaborations these firms can access (international) academic networks and increase their status among customers, suppliers, and other relevant stakeholders, which often hold academic institutions in high esteem.

Collaborations with entrepreneurial ventures are beneficial for universities alike. In the context of these collaborations, university researchers can test the practical applications of their research, gain real-world insights on how to orient their future inquiring, and secure money to fund their projects (Etzkowitz and Leydesdorff 2000; Etzkowitz et al. 2000; Lee 2000).[2] In addition, more and more universities are currently setting up seed funds to finance promising entrepreneurial ventures (Munari et al. 2018). Collaborations with entrepreneurial ventures can help in the screening of ventures to be financed through these university seed funds.

Despite the aforementioned benefits, both entrepreneurial ventures and universities incur substantial costs when forming a first match. First, both parties must *invest time and effort in scouting potential partners*. Entrepreneurial ventures suffer several drawbacks in this endeavor. Due to their young age, entrepreneurial ventures have scant (or even no) experience in inter-organizational collaborations to guide their search; their founders must

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[2] It is nowadays rather common that national and international governmental bodies issue calls for research grants that encourage collaborations between universities and small and/or young firms. For instance, in the Horizon 2020 program funded by the European Commission, several instruments have been designed to increase the participation of small-medium enterprises to research projects that typically include also universities (see Factsheet: SME in Horizon 2020 at: https://ec.europa.eu/research/horizon2020/pdf/press/fact_sheet_on_sme_measures_in_horizon_2020.pdf).

focus attention on the venture core business[3] and have no time to directly search for university partners (Colombo et al. 2012a. See also Rosenkopf and Almeida 2003, for a similar argument). At the same time, entrepreneurial ventures have few resources for setting up strategies tailored to this search (e.g., dedicated hiring personnel or organizing dedicated events). In turn, universities find it hard to assess the quality and reliability of entrepreneurial ventures with which to form first matches because of the informational opaqueness, which typically characterize these firms (Berger and Udell 1998).

Second, in forming collaborations, entrepreneurial ventures and universities face the costs of bridging the differences—in terms of cultures, values, habits, norms, rules, practices, incentives, languages, and codes (Almeida et al. 2011; Gittelman and Kogut 2003)—separating the industrial and the academic worlds. Differences in the approach to knowledge dissemination are a case in point. University researchers have strong incentives to engage in knowledge dissemination as universities tie their careers to their success in publishing their research (Allen 1977; Stephan 1996). Conversely, the competitive advantage of entrepreneurial ventures—and, in general, of any firm—largely relies on the exclusive use of private knowledge (Liebeskind 1996; Spender 1994). Accordingly, firms fight to protect their knowledge through intellectual property rights (IPRs) and/or other market and non-market mechanisms. In firm-university collaborations, these two approaches clash. University researchers are eager to publish the results of the collaborative research in scientific journals; in turn, entrepreneurial ventures fear that these publications cause *appropriability hazards* (Oxley 1997) and unintended knowledge leakages to the benefit of competitors.

Third, when establishing a first match, entrepreneurial ventures and universities are mutually exposed to the risk of *opportunistic behaviors* (Williamson 1979; 1991). Because of the high uncertainty and information asymmetries (Almeida et al. 2011; Bercovitz and Feldman 2007) in the goals and the activities of these collaborations, entrepreneurial ventures' founders can hardly tell whether university researchers devote time and effort to solve commercially-relevant problems or, instead, they just focus on scientifically relevant issues (e.g., Lerner and Malmendier 2010). In turn, universities run the risk that entrepreneurial ventures opportunistically use the knowledge generated during the collaboration. As the collaboration unfolds, entrepreneurial ventures may withhold relevant information to independently file for a patent once the collaboration ends, thus securing the exclusive and unilateral use of collaborative knowledge. This may displease universities, which have recently become more attentive to secure IPRs on the knowledge they generate (Siegel et al. 2004). Clearly, collaborating partners can mitigate the risks of opportunism (and the associated costs) through contractual safeguards (Williamson 1985). As a matter of fact, university–industry contracts usually specify the beneficiaries of IPRs developed out of the collaboration, contain clauses that grant firms pre-publication review or force academic personnel to delay the publication of results until IPRs are secured (Bercovitz and Feldman 2007). However, setting up these contractual safeguards is costly; for instance, it requires a competent legal staff and resources for suing the opportunistic partner(s) in court. This is rather infrequent in the context of collaborations between universities and entrepreneurial ventures, as these latter often lack resources for setting up a legal staff and defending their IPRs in court.

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[3] The literature states that entrepreneurial ventures founders are time-constrained (e.g., Baron et al. 1999; Colombo and Grilli 2013; Sine et al. 2006).

3 Research hypotheses

Basing on the discussion in Sect. 2.1, we conclude that the probability of the first match between an entrepreneurial venture and a university increases in the presence of factors that enhance the benefits and lower the costs of forming a collaboration. In particular, we argue that the *individual social ties*, which entrepreneurial ventures' founders have formed by working as professors or researchers in a given university before incorporating their ventures, rank prominently among these factors. In so doing, as noted in the introduction, we adhere to the research tradition, which stresses the importance of individuals' social ties (and social structures) in shaping economic outcomes (Blau 1977; Granovetter 2005). Moreover, we expand on contributions, which recognize the importance of ties formed out of prior work experience in triggering collaborations between organizations (e.g., Brass et al. 2004; Broekel and Boschma 2012).

First, individual social ties reduce the costs, which both parties must bear for scouting for potential partners (Almeida et al. 2011). Indeed, when searching for partners to establish their first university collaboration, the founders of an entrepreneurial venture can easily contact their former academic colleagues or ask them to be referenced to other researchers from the same university.[4] These (direct and indirect) contacts allow to quickly evaluate the quality of the university research and its fitness with the venture's core business (Stuart et al. 2007). These social ties help also the university to assess the quality and reliability of the entrepreneurial venture. Indeed, professors and researchers of the focal university likely have a first-hand knowledge about the entrepreneurial venture incorporated by their former colleagues. They have probably seen for themselves the hatching of the business idea, the founders' efforts to develop it, and the value of the entrepreneurial team (e.g., Corredoira and Rosenkopf 2010).

Second, individual social ties have likely created a *common ground* between entrepreneurial venture's founders and their former academic colleagues. Scholars define common ground as the sum of mutual, common or joint knowledge, beliefs and suppositions among two (or more) individuals (Clark 1996, p.93), which makes it possible to anticipate and interpret accurately each other's actions. Common ground between entrepreneurial ventures' founders and university researchers favors knowledge transfer between the two parties and reduces the risk of conflicts (Puranam et al. 2009).

Third, evidence exists that social ties formed through shared work experience breed interpersonal trust (Rousseau et al. 1998),[5] which enhances the benefits and reduces the costs of collaborating. Trust facilitates knowledge transfer (Boschma 2005) and mitigates conflicts (Zaheer et al. 1998). Furthermore, it substitutes for costly formal governance mechanisms in shielding the parties against each other's opportunism. In particular, trust makes parties able to coordinate by mutual consent and, thus, reduces the need of including detailed clauses (e.g., for dealing with unexpected contingencies) in the contract ruling the collaboration (Poppo and Zenger 2002; Zaheer et al. 1998). Along this line of reasoning, Bruneel et al. (2010) find that the existence of trust between firms and universities lowers the perceived costs of negotiating legal clauses, which is a barrier to firm-university

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[4] Referral by a common acquaintance is a well-known mechanism of social tie formation, which is rather used in the context of entrepreneurial ventures (Hite and Hesterly 2001).

[5] In this paper, we adhere to the classical definition of trust as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behaviour of another" (Rousseau et al. 1998, p.394).

collaborations. Finally, trust renders less compelling for the parties to set up complex monitoring mechanisms.

Basing on the discussion above, we conclude that the presence of individual social ties induces entrepreneurial ventures and universities to view a first match between them as having higher benefits and lower costs than it would have happened in absence of these ties; thus, increasing the probability of its formation. Hypothesis H1 follows.

H1 The probability of a first match between an entrepreneurial venture and a university increases if the entrepreneurial venture's founders have individual social ties within that university.

Let us now focus on the factors that weakens the relation sub H1, thus, reducing the importance of founders' individual social ties. Scholars agree that, *ceteris paribus*, geographical proximity facilitates the formation of firm-university collaborations—and in general of inter-organizational collaborations—by enhancing their benefits and lowering their costs (e.g.Mansfield and Lee 1996; McKelvey et al. 2003; Ponds et al. 2007). In the following, we argue that geographical proximity between a venture and a university diminishes the role of founders' individual social ties in favoring the first match between the two parties; in other words, geographical proximity substitutes of individuals' social ties.

First, geographical proximity enables frequent *face-to-face interactions* between the collaborating parties. These interactions favor the absorption of tacit knowledge (Gertler 2003), which is a prominent component of university knowledge as this knowledge is just partially formed and often is no more than an "early-stage proofs of concept" (Gittelman 2007; Morgan 2004). Furthermore, face-to-face interactions allow the entrepreneurial ventures' personnel and their academic counterparts to develop common ground and trust, even in absence of individual social ties from prior shared work experience (Boschma 2005; Rosenkopf and Almeida 2003). In turn, as discussed while illustrating H1, common ground and trust increase the benefits and reduce the costs of starting a collaboration.

Second, geographical proximity reduces the costs, which both parties have to bear for scouting potential partners. Neither entrepreneurial ventures nor universities must spend money in long distant travels if they want to meet for deciding whether to form a collaboration. This creates opportunities to establish collaborations out of the traditional social networks and structures to which university researchers and ventures' founders belong (Blau 1977, p. 42).

Third, when universities and entrepreneurial ventures are geographically proximate, their embeddedness within the same local context increases the benefits and reduces the costs of forming first matches. Indeed, universities can leverage their strong local connections (e.g., Spigel 2017) to easily acquire information on the quality and reliability of the entrepreneurial ventures, with which they are considering to match. Likewise, the entrepreneurial ventures' embeddedness into the local context makes them less prone to indulge in opportunistic behaviors. Indeed, such an embeddedness exposes opportunistic ventures to the risk of acquiring a bad reputation within this context and thus suffering negative consequences in terms of resource acquisition (see Ghio et al. 2019 for a detailed discussion of this issue).

Based on the discussion above, we expect that the positive effect of individual social ties in increasing the probability of a first match (H1) weakens when an entrepreneurial venture and a university are geographically proximate. As discussed above, geographical proximity facilitates knowledge transfer, reduces the costs of scouting for partners, creates common ground,

breeds trust, act as a disciplinary device against opportunistic behavior. Recalling the arguments supporting H1, we can conclude that geographical proximity engenders effects similar to those caused by the presence of individual social ties of entrepreneurial venture's founders within the focal university. In other words, one should expect that geographical proximity is especially important for the formation of a first match, when founders' social ties do not exist, and vice-versa.

The discussion above leads us to formulate Hypothesis H2.

H2 Geographical proximity between an entrepreneurial venture and a university weakens the positive association between the probability of a first match and the presence of individual social ties of entrepreneurial venture's founders within that university.

Finally, we consider another important dimension of proximity—*cognitive proximity*—as a second moderating factor of the relation sub H1. As noted in the introduction, Boschma (2005) defines cognitive proximity between two organizations as the level of similarity between their knowledge bases. Cognitive proximate organizations perceive, interpret, understand, and evaluate the world in similar ways (Wuyts et al. 2005). We argue here that cognitive proximity increases the benefits and reduces the cost for entrepreneurial ventures and universities of starting a collaboration. Therefore, cognitive proximity substitutes for the existence of social ties between ventures' entrepreneurs and the personnel of universities, making these ties less fundamental for the establishment of an initial collaboration between ventures and universities.

First, cognitive proximity favors knowledge transfer between the two collaborating organizations. Indeed, the presence of a common knowledge base, facilitates mutual understanding and enables shared learning (e.g., De Jong and Freel 2010; Nooteboom et al. 2007; Villani et al. 2017). Cognitive distant organizations are instead less efficient in absorbing each other's knowledge because their knowledge roots in diverse norms, principles, and concepts (Rosenkopf and Almeida 2003). Furthermore, cognitive proximity reduces the conflicts arising from collaborations; it is a solid basis for the development of common ground (Muscio and Pozzali 2013) and of (competence-based) trust (Nooteboom 1996). Cognitive proximity also facilitates the scouting for potential partners. Indeed, knowledge similarity makes both universities and entrepreneurial ventures better able to judge the pros and cons of a possible collaboration.

In sum, as geographical proximity, cognitive proximity engenders effects, which are similar to those of founders' individual social ties. Accordingly, these ties are likely less relevant for the formation of a first match when cognitive proximity between entrepreneurial ventures and universities is high; conversely, the presence of these ties does matter when cognitive proximity is low. Hypothesis H3 follows.

H3 Cognitive proximity between an entrepreneurial venture and a university weakens the positive association between the probability of a first match and the presence of individual social ties of entrepreneurial venture's founders within that university.

4 Data

To test our hypotheses, we take advantage ofthe RITA (Research on Entrepreneurship in Advanced Technologies) directory, developed by the Entrepreneurship, Finance and Innovation research group (EFI Group, www.efi.polimi.it) at Politecnico di Milano. "Appendix 1" reports all the details of the construction of the RITA directory. In brief, the directory maps—through several waves of surveys and secondary sources—the activity of Italian new technology-based firms, defined as growth-oriented, independently owned businesses operating in high-tech industries[6] and established for no more than 25 years (Storey and Tether 1998). In the absence of reliable data on Italian new technology-based firms from official statistics,[7] the RITA directory is likely the most authoritative source of information on these firms; it has been used in many studies in the field of entrepreneurship and entrepreneurial finance (e.g., Bertoni et al. 2011; Colombo and Grilli 2010, 2013; Colombo et al. 2020).

The information contained in RITA and relevant for this study includes: firms' industry of operation, year of foundation, address, founders' identity and their individual characteristics (notably, founders' prior work experience). In the first semester of 2009, the EFI group sent a questionnaire (i.e., the RITA 2009 survey) to the 1646 firms[8] contained in the RITA directory as to January 1st 2009 for studying, among other things, their collaboration strategies; the questionnaire also included questions about university collaborations over the period 2004–2008. EFI research assistants eliminated discrepancies in data through phone interviews with the contact founders and compared the responses with information obtained from firms' website and other secondary sources. All this assured high data reliability.

To obtain a measure of university–industry collaboration, we based on the responses to five questions that asked whether the focal venture (1) obtained licenses from one or more universities, (2) used technical (non-patented) knowledge developed within universities, (3) financed joint R&D projects with universities, (4) used university laboratories and equipment, and (5) purchased consulting services from universities. We thus considered as "collaborating" a venture that engaged in at least one of the aforementioned collaboration forms in the period 2004–2008. The RITA 2009 survey also asked the names of the collaborating universities and the year in which each collaboration started.

We obtained complete information on university–industry collaborations for 453 ventures out of the aforementioned 1646 firms in the RITA directory (response rate: 27.52%).[9] As this study focuses on the *first matches* between *entrepreneurial ventures*

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[6] These industries are: computers; electronic components; telecommunication equipment; optical, medical and electronic instruments; biotechnology; pharmaceuticals; advanced materials; aerospace; robotics and process automation equipment; component and equipment for energy production; software; Internet; telecommunication services; environmental services; and R&D and engineering services.

[7] In Italy, a non-negligible portion of individuals who are defined as self-employed by official statistics actually are salaried workers with atypical employment contracts (especially in sectors like software). Unfortunately, on the basis of official data such individuals cannot be distinguished from funders of a venture. In addition, official statistics do not distinguish ventures that were established by one or more entrepreneurs from firms that were created as subsidiaries of other firms.

[8] The questionnaire was sent to the personal e-mail address of entrepreneurial ventures' founders, who acted as contact persons.

[9] Note that this sample is representative of the RITA population by geographical area ($\chi^2(3) = 0.26$), industry ($\chi^2(3) = 7.44$), and age ($\chi2(2) = 5.59$).

Table 1 Distribution of entrepreneurial ventures by industry, age and location

	Collaborating firms		Non-collaborating firms	
	N	%	N	%
Industry				
High-tech manufacturing	26	37.1	91	40.4
Pharmaceuticals and biotechnology	13	18.6	10	4.4
Software, Internet and telecommunication services	18	25.7	112	49.8
Other high-tech services	13	18.6	12	5.3
Total	70	100.0	225	100.0
Age				
Less than 3 years old	31	44.3	57	25.3
Between 3 and 6 years old	27	38.6	78	34.7
More than 6 years old	12	17.1	90	40.0
Total	70	100.0	225	100.0
Location				
North Est	14	20.0	47	20.9
North West	21	30.0	91	40.4
Center	19	27.1	44	19.6
South and Islands	16	22.9	43	19.1
Total	70	100.0	225	100.0

"High-tech manufacturing" includes aerospace, chemicals and advanced materials, telecommunication equipment, computers, electronic components, components and equipment for energy production, optical, medical and electronic instruments, and robotics and process automation. "Other high-tech services" includes R&D and engineering services, and environmental services

and universities, we consider only firms that: (1) were younger than 10 years in 2008 (see Almeida et al. 2003, for a similar approach) and (2) did not established prior collaborations with universities before 2004.[10] Therefore, the final sample consists of 295 high-tech entrepreneurial ventures. Between 2004 and 2008, seventy entrepreneurial ventures out of the 295 (23.73%) matched for the first time with one or more Italian universities, whereas 225 entrepreneurial ventures (i.e., 295–70, 76.27%) did not. Since some ventures engaged in a multi-partner collaboration, namely formed a first match with more than one Italian university,[11] we recorded 81 entrepreneurial venture-university realized collaborations. Table 1 reports the distribution of entrepreneurial ventures in our sample by geographical location, industry, and age (as of 2008). We also distinguish collaborating from non-collaborating ventures. The distributions of the two samples differ significantly across industries

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[10] The literature is not unanimous when defining entrepreneurial ventures (Nightingale and Coad 2014). Nevertheless, we acknowledge that the use of the 25-year threshold used to include firms in the RITA directory is questionable to identify *young* firms. Thus, we include in our sample (independent) firms of less than 10 years (Almeida et al. 2003). However, the results are similar when using a 25-year threshold, and they are available from the authors upon request.

[11] Projects funded under the Framework Programs for Research and Technological Development of the European Commission are a good example of these multi-partner collaborations.

$(\chi^2(3) = 62.77)$ and age classes $(\chi^2(2) = 19.37)$: collaborating ventures are younger (average age: 3.51) than non-collaborating ones (average age: 5.19), and they are more concentrated in pharmaceutics and biotechnology. No statistically significant differences emerge across geographical areas $(\chi^2(3) = 4.49)$.

We combined the aforementioned data on entrepreneurial ventures with data on Italian universities. Specifically, we focus on the 80 research-active Italian universities, according to the definition reported in the EUMIDA database on European Higher Education Institutions (European Commission 2010). For these universities, we extracted from the database of the Italian Ministry of Research (*Ministero dell'Università e della Ricerca*, MUR) data on the academic staff (full, associate, and assistant professors) in the period 2004–2008. Data on academic staff are disaggregated according to the 14 disciplinary areas defined by MUR: (1) Mathematics and computer sciences; (2) Physics; (3) Chemistry; (4) Earth sciences; (5) Biology; (6) Medicine; (7) Agricultural and veterinary sciences; 8) Civil engineering and architecture; (9) Industrial and information engineering; (10) Philological-literary sciences, antiquities, and arts; (11) History, philosophy, psychology and pedagogy; (12) Law; (13) Economics and statistics; and (14) Political and social sciences. Moreover, to assess the quality of the universities, we used data from the 2004–2010 Italian research assessment exercise (*Valutazione della Qualità della Ricerca*, VQR), conducted by the National Agency for the Evaluation of Universities and Research Institutes, (ANVUR, http://www.anvur.org). More precisely, the VQR assessed the quality of the research products (i.e., journal articles, monographs, essays, conference proceedings, patents, software and databases) produced in the period 2004–2010 by personnel of universities and public and private research institutions supervised by MUR. For each of the aforementioned disciplinary areas, the ANVUR set up a group of experts that evaluated more than 180,000 research products resorting to peer review methods and bibliometric analyses.

Finally, we used Google Maps to retrieve latitude and longitude of entrepreneurial ventures and universities.

5 Method

The econometric specification consists of a two-stage Heckman procedure (Heckman 1979). In the first stage, we estimate the probability that an entrepreneurial venture establishes a first match with *any* university in the period 2004–2008; the unit of analysis in this first stage is the entrepreneurial venture (295 observations). In the second stage, we estimate the probability of the first match between *the entrepreneurial venture i and the university j*; the unit of analysis in this second stage is the entrepreneurial venture-university dyad. Specifically, we consider 5600 entrepreneurial venture-university dyads resulting from all the possible combinations between the 70 collaborating entrepreneurial ventures and the 80 Italian research-active universities with which an entrepreneurial venture might have potentially matched. In the second stage, we include the inverse Mills ratio resulting from the first stage to account for the possible sample selection bias associated with the exclusion of non-collaborating ventures.[12] Diestre and Rajagopalan (2012) resort to a

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[12] In a robustness check, we consider all the 295 collaborating and non-collaborating entrepreneurial ventures (in these estimates we drop the inverse Mills ratio). See Sect. 5.2 for further details.

similar approach for studying the formation of collaborative ties between biotechnology start-ups and incumbents in the pharmaceutical industry.

5.1 First stage of the Heckman model

The dependent variable of the first stage of the Heckman model is the dummy *collaborating$_i$*, which equals 1 for the 70 entrepreneurial ventures that, in the period 2004–2008, collaborated for the first time with one or more universities and 0 for the 225 non-collaborating ventures. Due to the binary nature of the dependent variable, we resort to a Probit specification. Independent variables, which likely relate to the probability that an entrepreneurial venture collaborates with a university, include: the venture's age as in 2008 (*age$_i$*); the number of its founders (*founders$_i$*); and four dummy variables that equals 1 if the venture (1) is a limited liability company (*limited$_i$*); (2) is an academic spin-off (*academic spin-off$_i$*),[13] (3) has been located in a business incubator (*incubator$_i$*) and (4) is located in a geographical area (NUTS3, http://ec.europa.eu/eurostat/web/nuts) where there is at least one university that produces high-quality research in the disciplinary areas that are relevant for the entrepreneurial venture (*quality$_i$*). The variable *quality$_i$* is computed through the same approach that we used for computing the variable *quality$_{i,j}$* at the dyad-level in the second-stage estimates (see Sect. 4.2 for details).

Furthermore, we include a measure of industrial clustering (*cluster$_i$*), defined as the ratio between the total number (as in 2004) of high-tech entrepreneurial ventures[14] in the same NUTS3 area of the focal venture and the size (in square km) of this NUTS3 area. Finally, we add entrepreneurial ventures' industry and geographical area (NUTS1) dummies.

Table 2 reports the description of the variables used in the first stage, Table 3 contains the summary statistics of these variables and their correlation matrix.

5.2 Second stage of the Heckman model

The second stage of the Heckman model is our main econometric model, through which we test hypotheses H1–H3. Its specification is as follow:

$$P\big(first\ match_{i,j} = 1\big) = g\big[prior\ academic\ work\ experience_{i,j}, \log{(distance)_{i,j}}, knowledge\ base_{i,j}, Z_{i,j}\big] \tag{1}$$

The dependent variable, *first match$_{i,j}$*, is a dummy variable that equals 1 if entrepreneurial venture *i* formed a first match (i.e., collaborated for the first time) with university *j* in the period 2004–2008. To test H1, we include the dummy variable *prior academic work experience$_{i,j}$*, which assesses the presence of individual social ties in university *j* by the founders of entrepreneurial venture *i*. It equals 1 if at least one of the founders of entrepreneurial venture *i* worked as a post-doc, assistant, associate or full professor in university *j* before incorporating venture *i*.

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[13] We define an academic spin-off as a venture that has a university among its shareholders and/or one or more founders with prior academic work experience as a post-doc, assistant, associate, or full professor (Pirnay and Surlemont 2003).

[14] Data on young high-tech firms as in 2004 come from the database of the Italian Chambers of Commerce. Data on the size of NUTS3 areas come from the Italian National Statistical Office (ISTAT).

Table 2 Description of the dependent and independent variables used in the first stage of the Heckman model

	Variable	Description
(1)	$collaborating_i$	Dummy variable that equals 1 if an entrepreneurial venture has established a first collaboration with one or more universities in the period 2004–2008, 0 otherwise
(2)	age_i	Entrepreneurial venture's age as in 2008
(3)	$founders_i$	Number of entrepreneurial venture's founders
(4)	$limited_i$	Dummy variable that equals 1 if an entrepreneurial venture is a limited liability company, 0 otherwise
(5)	$academic\ spin\text{-}off_i$	Dummy variable that equals 1 if an entrepreneurial venture is an academic spin-off (i.e., it has one university among its shareholders and/or one of more founders with prior academic work experience), 0 otherwise
(6)	$incubator_i$	Dummy variable that equals 1 if the entrepreneurial venture has been located in a business incubator, 0 otherwise
(7)	$quality_i$	Dummy variables that equals 1 if the entrepreneurial venture is located in a geographical area (NUTS3) in which there is at least a university that produces high-quality research in disciplinary areas, which are relevant to the industry of the entrepreneurial venture, 0 otherwise
(8)	$cluster_i$	Ratio between the total number of high-tech entrepreneurial ventures (as in 2004) operating in the same NUTS3 area in which the entrepreneurial venture is located to the size of the NUTS3 area (in square km)

Table 3 Summary statistics and correlation matrix of variables used in the first stage of the Heckman model

	Variable	Mean	Std. Dev	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	$collaborating_i$	0.237	0.426	0	1	1.000							
(2)	age_i	4.793	3.087	0	10	− 0.231	1.000						
(3)	$founders_i$	3.166	1.721	1	13	0.336	0.029	1.000					
(4)	$limited_i$	0.722	0.449	0	1	0.275	− 0.133	0.210	1.000				
(5)	$academic\ spin\text{-}off_i$	0.251	0.434	0	1	0.504	− 0.210	0.386	0.202	1.000			
(6)	$incubator_i$	0.247	0.432	0	1	0.456	− 0.209	0.246	0.181	0.466	1.000		
(7)	$quality_i$	0.149	0.357	0	1	− 0.032	− 0.009	0.009	− 0.038	− 0.001	0.003	1.000	
(8)	$cluster_i$	0.635	0.928	0.020	2.935	0.025	0.141	− 0.029	0.148	− 0.089	− 0.040	− 0.127	1.000

The unit of analysis is the entrepreneurial venture (295 observations)

To test H2, we interact *prior academic work experience*$_{i,j}$ with log(*distance*)$_{i,j}$. The variable log(*distance*)$_{i,j}$ is the logarithm of the kilometric distance between entrepreneurial venture *i* and university *j* and is an inverse measure of geographical proximity between *i* and *j* (see Broekel and Boschma 2012, for a similar approach).

Likewise, to test H3, we interact *prior academic work experience*$_{i,j}$ with *knowledge base*$_{i,j}$. This latter variable measures the overlap between the knowledge bases of entrepreneurial venture *i* and university *j*, and it is a proxy for the level of cognitive proximity between the two potential collaborating partners. We built it basing on the findings of Cohen et al. (2002) and Schartinger et al. (2002), which show that the impact on industrial R&D of university knowledge developed in different academic disciplines differs across industries. We, therefore, used the above-mentioned studies to link the scientific/technological domain of university knowledge (according to the MUR classification of university disciplinary areas presented in Sect. 3) to the industry in which the entrepreneurial venture operates (see the "Appendix 2" for details). We then calculated the share of the academic staff of the university *j* that specializes in the disciplinary areas associated with the industry of the entrepreneurial venture *i*. The variable *knowledge base*$_{i,j}$ is thus defined as follows:

$$knowledge\ base_{i,j} = \sum_{d(i)} \left(\frac{academic\ staff_{j,d(i)}}{academic\ staff_j} \right); \tag{2}$$

where *academic staff*$_{j,d(i)}$ is the average number of full, associate, and assistant professors (i.e., the academic staff) enrolled in university *j* in the period 2004–2008 specializing in the disciplinary areas *d(i)*, which are associated with the industry of the entrepreneurial venture *i*, and *academic staff*$_j$ is the average total academic staff (i.e., in all disciplinary areas) enrolled in university *j* in the same period. If, for instance, entrepreneurial venture *i* operates in the medical equipment industry, we considered the share of the academic staff of university *j* that specializes in the disciplinary areas "Medicine" and "Industrial and information engineering".

The vector $Z_{i,j}$ includes several control variables to account for other factors affecting the probability of the first match between entrepreneurial venture *i* and university *j*. First, we control for the quality of the university knowledge produced in each disciplinary area pertinent to entrepreneurial venture *i* through the dummy variable *quality*$_{i,j}$. This variable equals 1 if university *j* produces high-quality research in at least one of the disciplinary areas that constitutes the knowledge base of the industry of entrepreneurial venture *i* (in accordance to what explained above). For each disciplinary area, we consider a university as producing high-quality research if the VQR assessment exercise ranked this university in the first quartile of the distribution of Italian universities of the pertinent university size segment.[15] In so doing, we avoid using a general research quality measure at the university level as similar studies (Hong and Su 2013; Laursen et al. 2011) do; instead, we rely on a specific and fine-grained measure, which accounts for the quality of the research in the disciplinary areas that are relevant to the focal venture.

Second, we control for university size by including in the regressions the average academic staff in thousands of units in the period 2004–2008 (*academic staff*$_j$). We

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[15] For each disciplinary area, the VQR produces three different rankings of Italian universities depending on the size of the university: small (less than 300 research products), medium (between 300 and 700 research products) and large (more than 700 research products).

Table 4 Description of the dependent and independent variables used in the second stage of the Heckman model

	Variable	Description
(1)	$first\ match_{i,j}$	Dummy variable that equals 1 if entrepreneurial venture i formed a first match with university j in the period 2004–2008, 0 otherwise
(2)	$prior\ academic\ work\ experience_{i,j}$	Dummy variable that equals 1 if at least one of the founders of entrepreneurial venture i had any academic work experience as a post-doc, assistant, associate or full professor in university j before the incorporation of the entrepreneurial venture, 0 otherwise
(3)	$\log(distance)_{i,j}$	Logarithm of the distance between entrepreneurial venture i and university j
(4)	$knowledge\ base_{i,j}$	Share of the academic staff (period 2004–2008) of university j that specializes in disciplinary areas, which are relevant to the industry of entrepreneurial venture i
(5)	$quality_{i,j}$	Dummy variable that equals 1 if university j produces high-quality research in at least one of the disciplinary areas, which are relevant to the industry of the entrepreneurial venture i, 0 otherwise
(6)	$academic\ staff_j$	Average academic staff of the focal university in the period 2004–2008
(7)	age_i	Entrepreneurial venture's age as in 2008
(8)	$cluster_i$	Ratio between the total number of high-tech entrepreneurial ventures (as in 2004) operating in the same NUTS3 area in which entrepreneurial venture i is located to the size of the NUTS3 area (in square km)
(9)	$academic\ spin\text{-}off_i$	Dummy variable that equals 1 if entrepreneurial venture i is an academic spin-off (i.e., it has one university among its shareholders and/or one of more founders with prior academic work experience), 0 otherwise

Table 5 Summary statistics and correlation matrix of variables used in the second stage of the Heckman model

	Variable	Mean	Std. Dev	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	$first\ match_{i,j}$	0.014	0.119	0	1	1.000								
(2)	$prior\ academic$ $work\ experience_{i,j}$	0.010	0.100	0	1	0.649	1.000							
(3)	$\log(distance)_{i,j}$	5.678	1.065	−1.050	7.006	−0.376	−0.338	1.000						
(4)	$knowledge\ base_{i,j}$	0.152	0.172	0	0.892	0.079	0.048	−0.028	1.000					
(5)	$quality_{i,j}$	0.264	0.441	0	1	0.033	0.038	−0.063	0.350	1.000				
(6)	$academic\ staff_j$	0.748	0.824	0.007	4.489	0.079	0.058	−0.016	0.127	0.099	1.000			
(7)	age_i	3.514	2.523	0	10	−0.001	−0.011	−0.033	−0.013	0.016	0.000	1.000		
(8)	$cluster_i$	0.677	1.015	0.020	2.935	−0.006	−0.033	−0.108	−0.018	−0.006	0.000	0.297	1.000	
(9)	$academic\ spin\text{-}off_i$	0.700	0.458	0	1	−0.009	0.066	0.022	−0.113	−0.076	0.000	−0.188	−0.263	1.000

The unit of analysis is the entrepreneurial venture-university dyad (5,600 observations)

Table 6 Results of the first-stage Probit regression of the Heckman model

	First stage regression
age_i	− 0.086**
	(0.040)
$founders_i$	0.164**
	(0.065)
$limited_i$	1.077***
	(0.386)
$academic\ spin\text{-}off_i$	1.146***
	(0.266)
$incubator_i$	0.731***
	(0.275)
$quality_i$	0.631*
	(0.368)
$cluster_i$	0.400***
	(0.143)
Constant	− 0.077**
	(0.038)
Industry and NUTS1 dummies (and their interactions)	Yes
N. observations	295
Log-likelihood	− 81.0
Pseudo R^2	0.50

Robust standard errors are in brackets

*, **, and ***Significance at the 10%, 5%, and 1% level, respectively. The dependent variable *(collaborating_i)* is a dummy variable that equals 1 if an entrepreneurial venture, in the period 2004–2008, collaborated for the first time with one or more universities, 0 otherwise

expect a positive coefficient for *academic staff_j* because larger universities are likely to enter more collaborations.

Third, we also include the age of the entrepreneurial venture in 2008 (age_i). In comparison with their younger counterparts, older entrepreneurial ventures likely have a larger network of potential partners and greater absorptive capacity (Cohen and Levinthal 1990). Thus, we expect that age_i has a positive coefficient.

Finally, we insert two controls that we also included in the first stage of the model: *cluster_i* and *academic spin-off_i*. The variable *cluster_i* captures that venture *i*'s location in a dense technological cluster may influence the first match between *i* and *j* (D'Este et al. 2013). Moreover, we expect that if an entrepreneurial venture is an academic spin-off, it should have a higher propensity to collaborate with one or more universities. Indeed, in comparison with other entrepreneurial ventures, academic spin-offs have higher institutional proximity with universities because they embed (some of) the cultural values and the norms of the academia (Ponds et al. 2007).

Table 4 reports the description of the variables used in the second-stage regressions at the dyad-level, and Table 5 contains the summary statistics and the correlation matrix of these variables.

Table 7 Results of the second-stage Probit regressions of the Heckman model

	1	2	3
prior academic work experience$_{i,j}$	2.700***	1.955***	3.733***
	(0.299)	(0.461)	(0.477)
log(*distance*)$_{i,j}$	− 0.421***	− 0.465***	− 0.444***
	(0.048)	(0.048)	(0.049)
knowledge base$_{i,j}$	1.383***	1.552***	1.683***
	(0.406)	(0.416)	(0.416)
prior academic work experience$_{i,j}$×log(*distance*)$_{i,j}$		0.245**	
		(0.120)	
prior academic work experience$_{i,j}$×*knowledge base$_{i,j}$*			− 4.100***
			(1.490)
university quality$_{i,j}$	− 0.154	− 0.193	− 0.149
	(0.165)	(0.165)	(0.164)
academic staff$_j$	0.273***	0.281***	0.270***
	(0.044)	(0.047)	(0.046)
age$_i$	0.003	− 0.000	0.015
	(0.026)	(0.027)	(0.026)
cluster$_i$	− 0.053	− 0.073	− 0.105
	(0.080)	(0.074)	(0.073)
academic spin-off$_i$	− 0.684***	− 0.697***	− 0.668***
	(0.146)	(0.141)	(0.147)
Inverse Mills ratio	0.309***	0.295**	0.307**
	(0.120)	(0.122)	(0.124)
Constant	− 1.094***	− 0.830***	− 1.098***
	(0.268)	(0.272)	(0.277)
Industry and NUTS1 dummies	Yes	Yes	Yes
N. observations	5600	5600	5600
Log-likelihood	− 163.8	− 161.2	− 159.1
Pseudo R^2	0.61	0.62	0.62

Standard errors are in brackets

** and ***Significance at the 5% and 1% level, respectively. The dependent variable (*first match$_{i,j}$*) is a dummy variable that equals 1 if entrepreneurial venture *i* has established a first match with university *j* in the period 2004–2008, 0 otherwise. Probit models with standard errors clustered at the entrepreneurial venture-level

6 Results

6.1 Main results

Table 6 reports the results from the first stage Probit regression on the probability that, in the period 2004–2008, an entrepreneurial venture collaborated for the first time with one or more universities. All coefficients of the independent variables are statistically significant at least at 5%, except for the coefficient of *quality$_i$*, which is significant at 10%.

Table 7 shows the results from the second-stage regressions of Eq. (1), through which we test our hypotheses on the probability that entrepreneurial venture *i* forms a first match
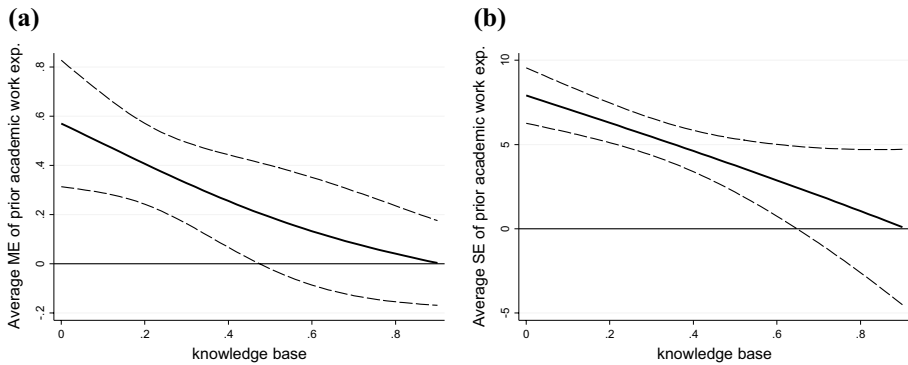
(a)   **(b)**
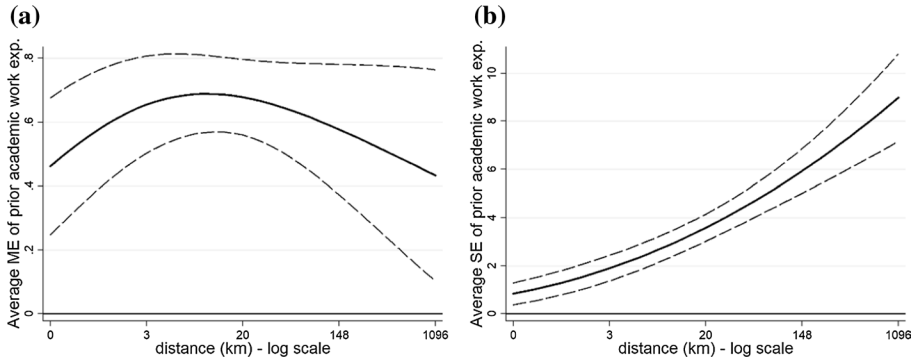
Fig. 1 Average marginal effect and semi-elasticity of prior academic work experience, as distance varies. Average marginal effect (**a**) and average semi-elasticity (**b**) of prior academic work experience of entrepreneurial venture *i*'s founders in the university *j*, as distance varies. The 95% confidence intervals (dashed lines) have been estimated by the delta method

with university *j*. Model 1 includes control variables and the main variables of interest (*prior academic work experience$_{i,j}$*, log(*distance*)$_{i,j}$ and *knowledge base$_{i,j}$*) without interactive terms. The results of the regressions obtained by adding the interactive term *prior academic work experience$_{i,j}$* × log(*distance*)$_{i,j}$ are shown in Model 2. Finally, Model 3 includes the interactive term *prior academic work experience$_{i,j}$* × *knowledge base$_{i,j}$*. In all estimates, the coefficients of the inverse Mills ratio are positive and significant at conventional confidence levels, thereby justifying the use of the two-stage Heckman model.

The results from Model 1 support hypothesis H1. The coefficient of *prior academic work experience$_{i,j}$* is indeed positive and significant at the 1% level. By working in a university before the incorporation of their venture, founders develop individual social ties, which, in turn, favor the match with that university. It is worth noting that the estimated effect is large in magnitude. In the absence of individual social ties (*prior academic work experience$_{i,j}$*=0), the estimated probability of the first match is 0.01, while it becomes 0.34 when *prior academic work experience$_{i,j}$*=1. Furthermore, Model 1 clearly highlights that both geographical and cognitive proximity substantially affects the probability of a first match. The coefficients of log(*distance*)$_{i,j}$ and *knowledge base$_{i,j}$* are indeed statistically significant at 1%. The lower the distance and the higher the overlap between the knowledge bases of entrepreneurial venture *i* and university *j*, the higher is the probability of the first match.

Let us now focus on Model 2, in which *log(distance)$_{i,j}$* is interacted with *prior academic work experience$_{i,j}$*. The interactive term is positive and significant at 5%, as expected according to hypothesis H2. Nevertheless, given the nonlinear specification of the Probit model, looking at the significance and the magnitude of the estimated coefficients is not sufficient to assess the impact of the variables of interest and the existence of moderating effects. To ascertain whether geographical proximity weakens the positive effect of founders' individual social ties in a given university on the probability of the first match, we report the average marginal effect (ME, in Fig. 1a) and the average semi-elasticity (SE, in Fig. 1b) of *prior academic work experience$_{i,j}$* as distance varies. The average ME is the average increase in the probability of the first match due to one unit increase in the variable of interest. The average SE is the average percentage increase in the abovementioned

(a)

(b)

Fig. 2 Average marginal effect and semi-elasticity of prior academic work experience, as knowledge base varies. Average marginal effect (**a**) and average semi-elasticity (**b**) of prior academic work experience of entrepreneurial venture *i*'s founders in the university *j*, as knowledge base varies. The 95% confidence intervals (dashed lines) have been estimated by the delta method

probability due to one unit increase in the variable of interest. MEs and SEs for different values of $log(distance)_{i,j}$ are calculated on the basis of the coefficients of Model 2. We consider increasing values of $log(distance)_{i,j}$, from -1 (the minimum value in the sample, corresponding to a distance of 0.4 km) to 7 (the maximum value in the sample, corresponding to a distance of 1,096 km) in increments of 0.2. The 95% confidence intervals (the dashed lines in Fig. 1) are estimated by the delta method.

As shown in Fig. 1a, the average ME of *prior academic work experience*$_{i,j}$ is positive and of large magnitude at any distance. It increases as the distance of an entrepreneurial venture from the focal university increases up to a distance of 16 km (i.e., $log(distance)_{i,j} = 2.8$), where it reaches its maximum of 0.68. Then, it decreases. Nevertheless, the average ME of *prior academic work experience*$_{i,j}$ when the distance is 100 km (i.e., $log(distance)_{i,j} = 4.6$) still is 0.59, a value that is higher than the corresponding value (0.46) when the distance is 0.4 km (i.e., $log(distance)_{i,j} = -1$, the minimum value in the sample). Furthermore, Fig. 1b clearly shows that the average SE of *prior academic work experience*$_{i,j}$ increases (decreases) with geographical distance (proximity). As *prior academic work experience*$_{i,j}$ switches from 0 to 1, the average percentage increase in the probability of the first match is $+83\%$ when the distance is 0.4 km. However, when the distance is 100 km, the average increase is $+540\%$. In other words, the positive effect of founder's social ties in a given university on the probability of a first match with that university is strong especially for long-distance collaborations, which are less likely to occur, while it is weakened by geographical proximity.

Let us now move to Model 3. The interactive term *prior academic work experience*$_{i,j}$ $\times$ *knowledge base*$_{i,j}$ is negative and significant at 1%, in line with hypothesis H3. Similar to what done in the case of distance, we also report the average ME (Fig. 2a) and the average SE (Fig. 2b) of *prior academic work experience*$_{i,j}$ as the overlap in the knowledge bases of entrepreneurial venture *i* and university *j* varies. Figure 2a shows that the ME of *prior academic work experience*$_{i,j}$ is at its maximum (0.57) when *knowledge base*$_{i,j}$ is zero, then it decreases as the overlap in the knowledge bases increases. For values of *knowledge base*$_{i,j}$ higher than 0.45 it becomes not significant (at 5%). Figure 2b exhibits a similar pattern, with an estimated SE of 791% when *knowledge base*$_{i,j}$ is zero. In other

Table 8 Additional robustness checks

	4a	5a	6a	7a	8a	9a
Panel A: Founders' social ties and geographical proximity						
prior academic work experience$_{i,j}$	1.823***	1.353***	1.877***	2.617**	3.260***	3.697***
	(0.476)	(0.372)	(0.290)	(1.278)	(1.045)	(0.332)
log(distance)$_{i,j}$	− 0.471***	− 0.492***	− 0.341***	− 1.712***	− 1.195***	
	(0.051)	(0.050)	(0.029)	(0.385)	(0.147)	
knowledge base$_{i,j}$	1.806***	1.612***	1.257***	3.362***	3.825**	1.387***
	(0.508)	(0.459)	(0.279)	(1.151)	(1.564)	(0.388)
prior academic work experience$_{i,j}$ × log(distance)$_{i,j}$	0.312**	0.408***	0.113	0.693**	0.707***	
	(0.123)	(0.100)	(0.079)	(0.321)	(0.274)	
university quality$_{i,j}$	− 0.288	− 0.148	− 0.138	− 0.519	− 1.569**	− 0.172
	(0.183)	(0.209)	(0.140)	(0.397)	(0.766)	(0.152)
academic staff$_j$	0.300***	0.241***	0.169***	0.625***		0.251***
	(0.050)	(0.070)	(0.038)	(0.118)		(0.041)
age$_i$	− 0.021	0.018	− 0.050**		0.035	0.001
	(0.032)	(0.027)	(0.023)		(0.079)	(0.024)
cluster$_i$	− 0.103	− 0.045	0.031		− 0.524	0.016
	(0.081)	(0.088)	(0.081)		(0.345)	(0.067)
academic spin-off$_i$	− 0.777***	− 0.691***	− 0.145		− 2.096***	− 0.668***
	(0.174)	(0.170)	(0.172)		(0.518)	(0.126)
size$_i$	0.409**					
	(0.199)					
geographical proximity$_{i,j}$						2.277***
						(0.314)
prior academic work experience$_{i,j}$ × geographical proximity$_{i,j}$						− 1.711***
						(0.618)

Table 8 (continued)

	4a	5a	6a	7a	8a	9a
Inverse Mills ratio	0.215**	0.107				0.266***
	(0.105)	(0.170)				(0.102)
Constant	− 0.720**	− 0.818***	− 1.605***			− 3.276***
	(0.313)	(0.296)	(0.203)			(0.191)
Industry and NUTS1 dummies	Yes	Yes	Yes	No	Yes	Yes
Industry and NUTS1 dummies×log(distance)$_{i,j}$	No	No	No	Yes	No	No
N. observations	5120	5600	23,120	5600	2520	5600
Log-likelihood	− 139.5	− 130.5	− 244.9	− 102.2	− 88.8	− 182.6
Pseudo R^2	0.64	0.63	0.55	0.70	0.70	0.57

	4b	5b	6b	7b	8b	9b
Panel B: Founders' social ties and cognitive proximity						
prior academic work experience$_{i,j}$	3.861***	2.841***	2.746***	7.457***	7.409***	4.148***
	(0.521)	(0.449)	(0.308)	(1.237)	(1.272)	(0.451)
log(distance)$_{i,j}$	− 0.434***	− 0.389***	− 0.327***	− 1.766***	− 1.129***	
	(0.051)	(0.048)	(0.029)	(0.458)	(0.143)	
knowledge base$_{i,j}$	1.921***	1.403***	1.430***	3.846***	3.734***	1.455***
	(0.498)	(0.396)	(0.277)	(1.192)	(1.504)	(0.379)
prior academic work experience$_{i,j}$×knowledge base$_{i,j}$	− 4.297***	− 1.847	− 2.323***	− 8.505**	− 7.418**	− 4.459***
	(1.557)	(1.518)	(0.858)	(3.577)	(3.433)	(1.519)
university quality$_{i,j}$	− 0.225	− 0.033	− 0.126	− 0.438	− 1.379***	-0.134
	(0.178)	(0.201)	(0.138)	(0.379)	(0.767)	(0.152)
academic staff$_j$	0.283***	0.215***	0.168***	0.589***		0.243***
	(0.049)	(0.066)	(0.038)	(0.125)		(0.041)
age$_i$	− 0.004	0.033	− 0.048**		0.054	0.012
	(0.029)	(0.025)	(0.023)		(0.079)	(0.023)

Table 8 (continued)

	4b	5b	6b	7b	8b	9b
$cluster_i$	− 0.121	− 0.020	0.008		− 0.618*	0.008
	(0.081)	(0.083)	(0.078)		(0.334)	(0.070)
$academic\ spin\text{-}off_i$	− 0.722***	− 0.623***	− 0.167		− 2.176***	− 0.640***
	(0.186)	(0.171)	(0.172)		(0.517)	(0.131)
$size_i$	0.367**					
	(0.183)					
$geographical\ proximity_{ij}$						2.059***
						(0.285)
Inverse Mills ratio	0.229**	0.089				0.290***
	(0.105)	(0.171)				(0.106)
Constant	− 1.077***	− 1.445***	− 1.704			− 3.422***
	(0.310)	(0.305)	(0.207)			(0.218)
Industry and NUTS1 dummies	Yes	Yes	Yes	No	Yes	Yes
Industry and NUTS1 dummies × $\log(distance)_{ij}$	No	No	No	Yes	No	No
N. observations	5120	5600	23,120	5600	2520	5600
Log-likelihood	− 138.5	− 137.2	− 242.1	− 101.3	− 89.6	− 182.0
Pseudo R^2	0.64	0.61	0.55	0.71	0.70	0.57

Standard errors are in brackets

*, **, and ***Significance at the 10%, 5%, and 1% level, respectively. The dependent variable (*initial tie$_{ij}$*) is a dummy variable that equals 1 if the entrepreneurial venture *i* has established a first match with the university *j* during the period 2004–2008. Probit models with control for entrepreneurial venture's size (Model 4), without entrepreneurial ventures that did not establish any technological collaboration with universities (Model 5), including both collaborating and non-collaborating entrepreneurial ventures (Model 6) and where $\log(distance)_{ij}$ is replaced with *geographical proximity$_{ij}$* (Model 9). Conditional logit regression models at the entrepreneurial venture (Model 7) and university (Model 8) levels

words, a more similar knowledge base makes founders' individual social ties in a given university irrelevant in decision of forming a match with that university. This evidence confirms that cognitive proximity weakens the positive effect of founders' social ties in a given university on the probability of a first match with that university.

As to the control variables, we find evidence of a positive association between university size and the probability of the first match. The coefficients of *academic staff$_j$* are indeed positive and significant at 1% in all models. Conversely, the coefficient of *academic spin-off$_i$* is negative and significant at 1% in all models. This result, together with the positive effect of *prior academic work experience$_{i,j}$* discussed above, reinforces the view that what matters for the first match between entrepreneurial venture *i* and university *j* is that *i*'s founders have developed social ties in university *j*. In absence of these ties, the mere fact that venture *i* is an academic spin-off does not help its matching with university *j*.

6.2 Robustness checks

We run several robustness checks to further validate our findings. Table 8 reports the results of these additional estimates. The Panel A of Table 8 shows the results from the regressions that aim at testing the interaction of founders' social ties with geographical proximity, while the Panel B of Table 8 refers to cognitive proximity.

In Models 4a and 4b, we include an additional control for the size of the entrepreneurial venture. In comparison with their smaller counterparts, larger entrepreneurial ventures have more resources to establish university collaborations; moreover, universities likely consider larger ventures as more reliable partners. We measure size with the turnover of the entrepreneurial venture as of 2004 or at the incorporation date if the venture was incorporated after 2004. Unfortunately, this information was available only for 64 collaborating entrepreneurial ventures; thus, these models run on 5,120 (64 ventures × 80 universities) dyads instead of the 5600 dyads of the main models. The coefficient of *size$_i$* is positive and statistically significant at 5% in both models, whereas the other coefficients are similar to those presented in Table 7.

In Model 5a and 5b, we exclude from the analysis entrepreneurial ventures that only purchased services from universities and did not establish any form of research or technological collaboration (11 entrepreneurial ventures). Namely, we focus only on the entrepreneurial ventures that (1) obtained licenses from one or more universities; (2) utilized technical knowledge developed within universities; and (3) financed joint R&D projects with universities. The results of these additional estimations are similar to those shown in Table 7, although the statistical significance of the interactive term *prior academic work experience$_{i,j}$ × knowledge base$_{i,j}$* is lower.

One may also wonder whether the exclusion in the second stage estimates of entrepreneurial ventures that did not collaborate with any university creates a bias in our estimates. The use of a two-stage Heckman procedure, with the inclusion in the second stage estimates of the inverse Mills ratio calculated from the first stage estimates, is right intended to control for this sample selection bias. However, we also re-run our regressions considering all 295 collaborating and non-collaborating ventures in our sample, while dropping the inverse Mills ratio control. The regressions, reported in Models 6a and 6b, now run on 295 × 80 = 23,600 dyads. The results concerning the main variables of interest are qualitatively similar to those presented in Table 7, although the statistical significance is lower.

One may also argue that unobserved characteristics at both the entrepreneurial venture and university levels drive our results. To address this potential problem, we used

an alternative estimation methodology (a conditional logit regression model). The conditional logit model allows us to control for entrepreneurial ventures' and universities' latent characteristics, conditioning out their fixed effects (Hosmer et al. 2013). Conditional logit model has been widely used in the literature on the formation of collaborative ties (e.g., Cassi and Plunket 2015; Colombo and Shafi 2016; Diestre and Rajagopalan 2012; Dushnitsky and Shaver 2009). Conditioning by university controls for latent universities' characteristics, but leads to a smaller sample as universities that do not collaborate with sample entrepreneurial ventures in the period of interest fall out. In contrast, when conditioning out entrepreneurial venture fixed effects, the sample size is not affected as all the entrepreneurial ventures in the second stage regression have at least one collaboration.[16] The results are shown in Models 7a and 7b (entrepreneurial venture-level fixed effects) and Models 8a and 8b (university level-fixed effects) and are similar to those presented in Table 7. The coefficients of *prior academic work experience*$_{i,j}$, and its interactive terms with log(*distance*)$_{i,j}$ and *knowledge base*$_{i,j}$ have the predicted signs and are significant at conventional confidence levels.

Finally, following D'Este et al. (2013), we replaced log(*distance*)$_{i,j}$ with a direct measure of geographical proximity (Models 9a and 9b). The variable *geographical proximity*$_{i,j}$ is defined as the inverse of the square root of *distance*$_{i,j}$, i.e., *geographical proximity*$_{i,j}$ = *distance*$_{i,j}^{-1/2}$. The pseudo-R^2 is lower with respect to the models presented in Table 7. However, the results obtained when using this measure confirm the findings presented in Sect. 5.1.

7 Discussion and conclusion

This work studies the drivers of *first matches*, namely of the formation of collaborations between universities and entrepreneurial ventures, which have never collaborated before. In line with the mainstream research, which states that social ties among individuals shape economic outcomes (Blau 1977; Granovetter 2005), we find that the presence of individual social ties between the founders of a given entrepreneurial venture within a given university increases the probability of a first match between the two organizations. This positive relation weakens when the entrepreneurial venture and the university are geographically and cognitively proximate. Indeed, geographical and cognitive proximities influence the benefits and costs of forming a first match, similarly to how founders' individual social ties do, thus rendering these ties less important.

The paper contributes to the literature in several respects. First, it adds to the ample debate on university–industry collaborations by explicitly focusing attention on *entrepreneurial ventures*, a group of firms, which mainstream literature on the topic has overlooked. In particular, this work examines how entrepreneurial ventures form their *first* university collaborations, an issue, which—as we discussed in the introduction, is both academically and practically relevant. To date, studies on this topic in the entrepreneurship field disregarded the drivers of collaborations—a notable exception is in Stuart et al. (2007), who explore the role of the academic connections of biotech startups' founders in entering

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[16] When conditioning by entrepreneurial venture, variables that do not vary at the entrepreneurial venture level are dropped (*age*$_i$, *cluster*$_i$, *academic spin-off*$_i$, industry and geographical area dummies). However, we added interactive terms of log(*distance*)$_{i,j}$ with industry and geographical area dummies. Similarly, when conditioning by university, *academic staff*$_j$ is dropped.

university collaborations—and mainly explore the consequences of these collaborations on ventures' performance (e.g., George et al. 2002; Motohashi 2005; Soh and Subramanian 2014).[17]

Second, our findings document the role of individuals and of the social ties, which they have formed through their prior work experiences, in the formation of inter-organizational collaborations when no prior organizational-level relations exist. In so doing, this work relates to the literature that investigates the implications of individuals' mobility across organizations (Almeida et al. 2011), and notably from universities to firms (Gittleman and Kogut 2003). Studies on this topic concur that movers—e.g., engineers or star scientists— act as conduits for inter-organization knowledge flows, favoring the emergence of collaborations and, ultimately, boosting their (joint) performance (Almeida and Kogut 1999).

Third, the entrepreneurship literature acknowledges the key role of founders' individual social ties for their ventures. These ties favor the entrance of new members into the entrepreneurial team, the attraction of the first employees, the formation of embedded relations with suppliers (e.g., Aldrich and Kim 2007; Forbes et al. 2006). This paper sheds light on another beneficial effect of founders' individual social ties: the fact that these ties help entrepreneurial ventures to connect with the academia. However, founders' individual social ties have a drawback: they tend to reproduce, at the ventures' level, the social structures to which founders belong. This may turn into a liability in that these social structures constraint the formation of (potentially superior) collaborations with organizations where founders have no ties. Such a limitation appears more worrisome as prior work emphasizes path dependency in the formation collaborations, with prior collaborations driving the subsequent ones (Brass et al. 2004).

Fourth, our results add to the research on the role of (different forms of) proximity in the formation of inter-organizational collaborations (Boschma 2005). Evidence exists that organizational-level proximities like geographical (e.g., D'Este and Iammarino 2010; Mowery and Ziedonis 2015), institutional (Ponds et al. 2007), and social proximities (in the form of prior partnerships, e.g., Hong and Su 2013) make organizations more inclined to collaborate. However, to the best of our knowledge, no study analyzes the relation between individual-level social ties and organizational-level proximities. We do so by showing that geographical and cognitive proximities between entrepreneurial ventures and universities weaken the importance of individual-level founders' social ties for the formation of a first match with a university collaborating partner. The superior knowledge transfer and the cost-reductions enabled by geographical and cognitive proximities give entrepreneurial ventures the opportunity to ground their first matches on their local context and on synergies arising from knowledge similarities, thus rendering them less dependent on the individual social ties of their founders.

As with any other study, this paper has limitations, which open up avenues for future research. First, we investigate the first matches between *entrepreneurial ventures and universities*, thus disregarding that these firms can turn attention to other types of organizations, when searching for collaborating partners. Collaborations with incumbents are a case in point, despite the "swimming with sharks" risk (Katila et al. 2008). Our two-step empirical specification controls for the presence of entrepreneurial ventures that did not

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[17] One should also note that these studies focus mainly on the biotech industries, this brings into question the generalizability of their results.

collaborate with universities. Conversely, we do not model entrepreneurial ventures' choice to form first matches with other types of organizations rather than with universities. Therefore, we welcome studies that consider this scenario.

Second, and partially related to the previous point, this work focuses on the first matches; basing on the imprinting concept, we conclude that these first matches likely influence subsequent matches. Future investigations should test this conjecture.

Third, our sample refers to collaborations between Italian high-tech entrepreneurial ventures and Italian universities. Such a focus on just one country may suggest that results depend on the characteristics of Italian high-tech industry and university system, thus calling into question the generalizability of our study. Hence, future studies should replicate our research in other countries and industries.

Forth, more and more universities are currently adopting proactive strategies for technology transfer (TT) and devote sizable amounts of resources to this activity, for instance by setting up TT offices (Fitzgerald and Cunningham 2016). We expect that universities' proactive TT strategies, especially if implemented by experienced managers (Kotha et al. 2018), ease the formation of first matches with entrepreneurial ventures, even in absence of founders' social ties in focal universities and of geographical and cognitive proximities. Unfortunately, we lack reliable data about the TT strategies of Italian universities, and thus, we leave the investigation of this aspect to further inquiry.

Fifth, we measure founders' social ties within a given university through founders' prior work experience in that university. However, founders can form social ties within universities in other ways. Engaging in joint patenting (Hong and Su 2013) and developing joint publications (e.g., Gittelman and Kogut 2003; Stuart and Ding 2006) are cases in point. In addition, ventures' founders and university researchers may form individual social ties during conferences, seminars, and networking events. Further research should compare the effectiveness of these diverse mechanisms of individual social ties' creation for the formation of first matches. For instance, are ties created out of academic work experience more effective than those formed through occasional social interactions?

Finally, despite founders' individual social ties increase the benefits and reduce the costs of forming first matches, they also bound entrepreneurial ventures' collaborations within their founders' social structures. Our results show that geographical and cognitive proximities make founders' individual social ties less important; but, again, they trap ventures into their local context and knowledge domain. Therefore, it would be of interest to study how the advantages and disadvantages related to our explanatory variables impact on the performance of these collaborations. Do collaborations driven by founders' individual ties perform better than those with universities where founders have no ties? Answering this research question is highly interesting considering also that collaborations enabled by individuals have high causal ambiguity (Almeida et al. 2011) and thus are less replicable by competitors. In addition, Boschma and Frenken (2010) use the term "proximity paradox" to highlight that proximity may hamper the innovative performance of collaborations. Is this negative effect at work also in case of entrepreneurial ventures for which the cost-reduction effects of geographical and cognitive proximities are highly valuable?

Despite these limitations, our results have meaningful implications for the design of policy schemes that support entrepreneurial venture-university collaborations. Entrepreneurial ventures are engines of innovation, new job creation, and economic development (Criscuolo et al. 2014) and collaborations with universities substantially contribute to their success

and growth (Acs et al. 2013; Bonaccorsi et al. 2014). However, significant barriers hamper university collaborations, especially when entrepreneurial ventures have never collaborated before. Thus, policymakers interested in supporting entrepreneurship must find ways to overcome these barriers. Our results suggest that initiatives that favor the formation of individual-level ties between ventures' founders and university personnel can be a (low cost) way to foster first matches. For example, policymakers might support the organization of workshops, training activities, and specialized social networks as a way to connect (both extant and prospective) entrepreneurs and academic personnel.[18] According to our findings, individual social ties are less important when entrepreneurial ventures and universities are geographically or cognitively proximate. Policymakers can help in this regard by favoring entrepreneurial ventures' relocation close to universities that have a scientific specialization coherent with their business. Provided that relocation is costly, university incubators can play a role here. Traditionally, these incubators have supported the creation of academic spin-offs, but evidence exists that incubators also foster collaborations between entrepreneurial ventures created by non-academics and universities (Colombo et al. 2012b). Consequently, policymakers may favor the relocation of ventures within university incubators, especially in the cases in which founders' lack individual social ties.

Appendix 1

The RITA directory was built at the end of 1999 and extended through subsequent waves in 2002, 2004, 2007, and 2009. Information on the 1646 firms included in the directory as of January 1st, 2009, was collected through the following procedure. First, the database of the national Chambers of Commerce was used to identify Italian firms founded since January 1st, 1983, remaining active on June 30th, 2008, and operating in the ATECO 2002 industry segments corresponding to the industries listed in Sect. 3. A population composed of 49,616 firms was identified. This population included both owner-managed and non-owner-managed firms. A stratified sample based on the province (NUTS3) in which the firms were located and their industry and composed of 14,395 firms was extracted from this population. With the aim of administering a survey to these firms, the EFI research group used the Internet to search for an email address and the name of a member of the entrepreneurial team (the firm contact person) for each firm. The research team obtained an email and a contact name for 5,848 firms and sent a questionnaire to the contact persons of these firms by either fax or e-mail. The team conducted several phone or face-to-face follow-up interviews to solicit answers to the questionnaire, obtain missing data and check that the collected data were reliable. For this purpose, the collected data were also cross-checked with information from secondary sources, when available. The EFI research group received 972 completed questionnaires related to owner-managed firms. Questionnaire from non-owner-managed firms (e.g. subsidiaries of other firms) were discarded. The 972 responding firms and the 49,616 firms in the initial population had similar distributions by

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[18] The *Osservatori Digital Innovation* (www.osservatori.net) initiative, successfully launched by the School of Management of Politecnico di Milano, is an interesting example. *Osservatori* are on-going practice-oriented research projects that provide practical knowledge on selected topics and aggregate a (both physical and virtual) community of entrepreneurs, managers, investors, policy makers and other practitioners interested in the specific topic, acting as a forum discussion and a channel for transferring best practices.

geographical area, but their distributions by industry were different: the percentage of firms in services was lower among respondent firms. A possible explanation for this difference is the following. As service industries are less capital intensive than manufacturing ones, service industries include more individuals who are defined as firms' owners in the database of the Italian Chambers of Commerce, but are actually salaried workers with atypical employment contracts.

Second, the RITA directory includes firms that were credible candidates for becoming large firms (i.e., growth-oriented firms). For this purpose, the EFI research group resorted to several additional information sources. These included lists provided by national industry associations, on-line and off-line commercial firm directories, lists of participants in industry trades and expositions, and firms mentioned by the national financial press and specialized magazines or studies. Through these sources, the team obtained an email and the name of a contact person for an additional 2144 firms and sent the questionnaire also to the contact persons of these firms. A total of 674 filled questionnaires were received. These firms are representative of the above-mentioned 2144 firms with respect to both industry and geographical area. The 674 respondent firms were added to the above-mentioned 972 respondents, thus leading to the final sample of 1646 high-tech, growth-oriented firms mentioned in Sect. 4.

Appendix 2

See Table 9.

Table 9 Link between the entrepreneurial venture's industry and university disciplinary areas

Entrepreneurial venture's industry	Cohen et al. (2002) industry	Cohen et al. (2002) scientific fields	Schartinger et al. (2002) industry	Schartinger et al. (2002) scientific fields	University disciplinary areas (MIUR)
Aerospace	Aerospace	Computer science; Mathematics; electrical engineering	NA	NA	Mathematics and computer sciences; Industrial and information engineering
Chemicals and new materials	Basic chemicals; miscellaneous chemicals; chemicals nec	Chemistry	Manufacturing of chemicals*	Chemistry; Other, inter-disciplinary technical sciences; Electrical engineering; Agriculture; Other, interdisciplinary natural sciences; Medical chemistry, physics, physiology; Pharmacy and toxicology; Clinical medicine	Chemistry
Communication equipment	Communication equipment	Computer science; electrical engineering	Manufacturing of electronics	Low level of interaction between scientific fields and industries	Mathematics and computer sciences; Industrial and information engineering
Computers	Computers	Computer science; mathematics; electrical engineering; mechanical engineering	Manufacturing of computers, office machinery	Low level of interaction between scientific fields and industries	Mathematics and computer sciences; Industrial and information engineering
Electronic components and semiconductors	Electronic components; Semiconductors and related equipment	Physics; mathematics; electrical engineering; mechanical engineering	Manufacturing of electronics	Low level of interaction between scientific fields and industries	Mathematics and computer sciences; Physics; Industrial and information engineering

Table 9 (continued)

Entrepreneurial venture's industry	Cohen et al. (2002) industry	Cohen et al. (2002) scientific fields	Schartinger et al. (2002) industry	Schartinger et al. (2002) scientific fields	University disciplinary areas (MIUR)
Environmental services	NA	NA	Waste water and refuse services	Other, interdisciplinary technical sciences; Hydrology and hydrography	Earthsciences
Equipment and components for energy production	General purpose machinery	Mathematics; mechanical engineering	Manufacturing of machinery	Engineering	Mathematics and computer sciences; Industrial and information engineering
Medical equipment	Medical equipment	Medical and health science	Manufacturing of medical, optical, precision instruments**	Electrical engineering; physics, mechanics and astronomy; surgery, anaesthesiology; clinical medicine	Medicine; Industrial and information engineering
Pharma and biotech	Drugs	Biology; chemistry; medical and health science	Manufacturing of chemicals*	Chemistry; other, inter-disciplinary technical sciences; Electrical engineering; Agriculture; other, interdisciplinary natural sciences; medical chemistry, physics, physiology; pharmacy and toxicology; clinical medicine	Chemistry; Biology; Medicine; Agricultural and veterinary sciences
Precision instruments	Precision instruments	Electrical engineering	Manufacturing of medical, optical, precision instruments**	Electrical engineering; physics, mechanics and astronomy; Surgery, anaesthesiology; clinical medicine	Industrial and information engineering

Table 9 (continued)

Entrepreneurial venture's industry	Cohen et al. (2002) industry	Cohen et al. (2002) scientific fields	Schartinger et al. (2002) industry	Schartinger et al. (2002) scientific fields	University disciplinary areas (MIUR)
R&D and engineering services	NA	NA	Research & Development	Mining, metallurgy; economics; electrical engineering; traffic and transport science; physics, mechanics and astronomy	Physics; Earth sciences; Civil engineering and architecture; Industrial and information engineering; Economics and statistics
Renewable energy	NA	NA	Production and supply of energy	Engineering; geodesy; other, interdisciplinary technical sciences; electrical engineering; construction techniques	Earthsciences Industrial and information engineering
Robotics and automation	General purpose machinery	Mathematics; mechanical engineering	Manufacturing of machinery	Engineering	Mathematics and computer sciences; Industrial and information engineering
Software and internet	NA	NA	Software and related activities	Other, interdisciplinary technical sciences; Mathematics and informatics	Mathematics and computer sciences; Industrial and information engineering
Telecommunication services	NA	NA	Post and telecommunication services	Electrical engineering	Industrial and information engineering

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

*Including both chemicals and pharmaceuticals

**Including both medical equipment and precision instruments

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