The Annals of Regional Science
https://doi.org/10.1007/s00168-022-01182-2

SPECIAL ISSUE PAPER

The relationship between R&D knowledge spillovers and employment entry

Nicolò Barbieri[1,2] · Laura Ramaciotti[1] · Ugo Rizzo[2,3]

Received: 8 January 2021 / Accepted: 13 August 2022

Abstract

Recent approaches to entrepreneurship seek to explain regional heterogeneity by exploring the link between knowledge endowment and new firm creation. There are two main gaps in this stream of research. First, entrepreneurship tends to be considered in terms of entry rates rather than in terms of job creation. Second, most empirical studies focus on relatively large geographical areas and overlook the distance at which knowledge externalities dissipate. The present paper exploits data on firms based in the Emilia-Romagna region (Italy) to show that private R&D spillovers are positively associated with the size at entry of innovative firms only for those located close to the R&D activities and that these spillovers dissipate at a few kilometres from the R&D source. Non-linearities are detected only for low-tech sectors.

JEL Classification L26 · R10 · L11

1 Introduction

New ventures, which are vectors of both job creation and job destruction, are at the crux of employment dynamics (Decker et al. 2014; Calvino et al. 2016). According to a recent OECD report on the dynamics of employment growth in Europe, 'only young businesses—predominantly small—create a disproportionate number of jobs' and 'entry explains most of the contribution to job creation, followed by start-ups (i.e. firms that are less than 3 years old)' (Criscuolo et al. 2014, p. 5). Thus, exploring to what extent the determinants of entrepreneurial activity contribute to job creation is essential to understanding regional development. The objective of the present work is

✉ Ugo Rizzo
ugo.rizzo@unife.it

1 Department of Economics and Management, University of Ferrara, Ferrara, Italy

2 Seeds, Ferrara, Italy

3 Department of Mathematics and Computer Science, University of Ferrara, Ferrara, Italy

Published online: 22 September 2022

to study the spatial contingencies that lead to successful entrepreneurship by focusing on the extent to which geographical distance moderates R&D knowledge spillovers.

This paper builds on the knowledge spillover theory of entrepreneurship (KSTE) (Audretsch and Keilbach 2007), which stresses that unappropriated knowledge leaking from knowledge production and knowledge diffusion activities is an important source of new venture emergence. The KSTE postulates that the level of entrepreneurship in a certain geographical area is driven by the amount of knowledge that is produced in that local environment and is left unexploited. That is to say, the amount of available and uncommercialised knowledge is a fundamental feature for explaining the heterogeneity of territories in terms of entrepreneurship (Armington and Acs 2002).

The KSTE builds on three main conjectures (Plummer and Acs 2014). The first is the *knowledge hypothesis*, which predicts that there is a positive relationship between the level of R&D expenditure and regional entrepreneurial activity. So far, this hypothesis has been extensively explored by the extant literature and has been corroborated by several studies from an empirical perspective (Audretsch and Keilbach 2007; Acs et al. 2009). The second hypothesis is the *commercialisation efficiency hypothesis,* according to which entrepreneurial activity is negatively affected by the concentration of incumbents as they are endowed with the capabilities to exploit knowledge flows. By being able to rapidly exploit unappropriated knowledge within a region, incumbents reduce the market opportunities for would-be entrepreneurs. Plummer and Acs (2014) provide empirical evidence for US metropolitan areas, showing that the presence of incumbents has a negative moderating effect on entrepreneurial activity. The third hypothesis on which the KSTE builds is the *localisation hypothesis*: knowledge spillovers are spatially located in close geographical proximity. This hypothesis derives from numerous studies within the economics of innovation literature that show how knowledge spillovers are locally constrained (e.g. Anselin et al. 1997), even though non-linearities in the transmission of knowledge across space have been highlighted in various instances (e.g. Bathelt et al. 2004; Spithoven et al. 2020). Despite its centrality, empirical evidence testing the localisation hypothesis in the context of the KSTE is absent. In particular, there is a lack of quantification related to what 'close proximity' means—that is, the distance at which knowledge spillovers can affect entrepreneurship. The present paper aims to fill these gaps.

To address our research questions, we draw on the stream of the literature that stands at the intersection between knowledge transfer and agglomeration economies, from which we derive two main propositions. First, knowledge transfer can either be the result of market-based or non-market-based exchange, with the latter involving higher degree of tacit knowledge. The absence of clear-cut evidence on the relationship between spillovers and entrepreneurship may suggest that agglomeration produces positive externalities for entrepreneurship in the very proximate area, but its effect decays rapidly with distance (Rosenthal and Strange 2003; 2005). The second proposition is that firms differ in playing the role of externality receivers (Cainelli and Ganau 2018; Cainelli et al. 2018), which acknowledges the specificities of new entrants in exploiting R&D knowledge spillovers. We discriminate entrants in terms of being in high-tech versus low-tech sectors, and manufacturing versus service companies. These distinctions are relevant as agglomeration externalities produce different effects on different types of economic activities, usually being higher for high-tech and for non-tradable sectors, but non-negligible for less innovative sectors (e.g. Greenstone et al. 2010; Moretti and Thulin 2013). Finally, we distinguish entrants in terms of size of entry. In this respect, an important advantage of the present paper—compared to the majority of existing studies that investigate the determinants of entrepreneurship—is the adoption of a continuous measure of entrepreneurship that captures the probability of higher levels of post-entry performance. That is, instead of focusing on the number of entrants in a particular territorial area, we measure entrepreneurship in terms of employment level at entry (i.e. number of working owners and employees) and relate this information to the characteristics of the local spatial environment surrounding the entrant firm. Several studies investigate to what extent post-entry performance is contingent upon entry characteristics (e.g. Geroski et al. 2010) and find that size at entry is strongly associated with the probability of successful development in the period following entry (e.g. Mata et al. 1995; Segarra and Callejon, 2002; Strotmann 2007). Moreover, size at entry is particularly relevant when research-intensive sectors are analysed, given their low survival rates (Segarra and Callejon 2002; Boyer and Blazy 2014). In other words, large new entrants are less likely to exit the market and are more likely to show better post-entry performance; this emphasises the importance of new entrants to the labour market since they provide a net share of job creation. Moreover, assuming that new firms emerging from R&D knowledge spillovers are more innovative than others and that they lead to higher levels of job creation and economic growth compared to less innovative firms (e.g. Geroski and Machin 1992; Coad and Rao 2008; Harrison et al. 2014), accounting for the probability of success at entry (as we do with our measure of entrepreneurship) is even more appropriate compared to the conventional indicators such as the number of new firms. Finally, our proxy for entrepreneurship allows us to disentangle the role of spillovers at a fine-grained level using distance-based measures around the localisation of entry, rather than within administrative borders.

Our results show that knowledge spillovers influence entrepreneurship (measured as size at entry) mostly in very close geographical proximity. This finding holds for more innovative sectors and services, whereas in low-tech sectors the size at entry is positively associated with R&D investments either in very close proximity or farther away from the sources of spillover. Moreover, as far as more innovative sectors are concerned, our results highlight that investments in R&D affect entry size only within a very short distance.

The paper is structured as follows. Section 2 reviews the KSTE literature and the proximity conjecture, as well as how this work contributes to this strand of research. Section 3 describes the dataset and the variables, and Sect. 4 presents the empirical analysis and discusses the results. Section 5 offers some concluding remarks.

2 Knowledge spillover theory of entrepreneurship and the proximity conjecture

At the heart of the KSTE stands the tenet that 'knowledge spillover entrepreneurship will tend to be spatially located within close geographic proximity to the source of knowledge actually producing that knowledge' (Audretsch et al. 2006, p.

29). The hypothesis builds on the public-good nature of knowledge and stresses that knowledge spills over due to the non-excludability of the access and exploitation of the information contained in it. Such knowledge is, however, considered to be available especially at close distances because it is transferred through local habits, customs, and frequent face-to-face interactions (e.g. Audretsch 1998). In addition, some studies highlight that knowledge is mostly transferred through market-based channels such as the mobility of individuals or technology purchases (Zucker et al. 1998b; Breschi and Lissoni 2001; Mowery and Ziedonis 2005). Despite the KSTE not distinguishing between these two channels of knowledge transfer, we will consider both mechanisms as they are often intertwined (Mowery and Ziedonis 2005) and potentially conducive to entrepreneurship.

Our main objective is to investigate the geography of knowledge spillovers and the extent to which they spur entrepreneurial activity. It is possible to derive insights on this topic by referring to the researches on the role of knowledge base for innovation of regions, and on the mechanisms through which knowledge flows between organisations. A vast literature provides evidence that regions differ widely in terms of R&D and innovation capabilities: innovation processes are path dependent and tend to cluster, increasing regional growth differences. Although R&D spillovers explain a relevant part of interregional differences in terms of innovation activities (Fritsch and Franke 2004), the capability of a region to gain from knowledge spillovers strictly depends on its absorptive capacity (Cohen and Levinthal 1990). For instance, Miguélez and Moreno (2015), grounding on the role of networks for the diffusion of knowledge, provide evidence that a main determinant of regional capability to attract inventors rests in its level of absorptive capacity, measured in terms of R&D expenditure. Spillovers are therefore mediated by the knowledge base of a region (Asheim et al. 2011; Abreu 2011), that is in turn shaped by the economic, social and cognitive contexts in which economic activities are embedded (Howells 2002). Moreover, higher levels of proximity are required to appropriate more context-specific knowledge (Rodríguez-Pose and Crescenzi 2008). As a result, entrepreneurship, as an economic activity, is also embedded in a cognitive, social and economic context (Qian 2018), that determines the mechanisms by which knowledge spillovers are exploited and where.

The role of spatial proximity in the transfer of knowledge across organisations has been largely investigated from both a theoretical and empirical perspective. A common finding is that knowledge transfer processes are triggered and particularly successful at close distances (Audretsch 1998; Howells 2002; Bahar et al. 2014). However, other studies emphasise that knowledge may also be transferred from less proximate environments (e.g. Brostrom, 2010; Uyarra 2010). For instance, Bathelt et al. (2004) depict a model of clustering based on two building blocks: on the one hand, a local buzz enables creating a shared ecology of habits, and on the other hand, a pipeline network of actors allows firms to acquire knowledge from distant environments. According to Berchicci et al. (2016), long distances increase the benefit of collaboration, but firms tend to engage in distant collaborations more rarely and only when the expected benefits are high. In line with these insights, Spithoven et al. (2020) find that universities secure large research contracts with firms located either very close or very far away from their location.

Despite different studies providing evidence of knowledge transfer over long distances (e.g. Berchicci et al. 2016; Spithoven et al. 2020) and acknowledging that random, freely available knowledge spillovers may be less frequent compared to market-based forms of knowledge transfer (Breschi and Lissoni 2001), knowledge-flow processes take place with higher frequency within close geographical proximity (e.g. de Jong and Freel 2010; Spithoven et al. 2021). Breschi and Lissoni (2009) show that the diffusion of technical, innovative knowledge across firms emerges from the mobility of inventors rather than from non-market forms of knowledge flows. However, inventor mobility tends to take place within close distances. With a similar perspective, Mowery and Ziedonis (2005) find that market-based channels of knowledge transfer from university to industry tend to benefit from close geographical proximity to a higher extent compared to non-market-based channels: the authors however argue that these results are motivated by the need to accompany market transfers with non-market knowledge transfers. Indeed, non-market-based knowledge flows have often been found to exert benefits only within spatial constraints (e.g. Audretsch and Feldman 1996; Feldman and Audretsch 1999), as in the case of new industry growth through the creation of new firms (e.g. Zucker et al. 1998a).

Therefore, the differences in the extent to which knowledge transfer exerts its benefits at various distances may depend on the nature and main channels through which such knowledge transfer takes place, and specifically on the need to transfer knowledge by means of non-market-based exchanges. The knowledge flow process that gives rise to new firm creation is a complex one: the entrepreneur or team of founders needs to master or acquire a variety of capabilities (Lazear 2005; Åstebro and Thompson 2011; Stuetzer et al. 2013), and the knowledge required to start a new business may be linked to some specific contexts. Successful entrepreneurs tend to be experienced individuals that have previous capabilities, both as employees and as precedent entrepreneurs (Lazear 2005; Åstebro and Thompson 2011), and this knowledge is often context specific. A good example of the role of context-specific knowledge in undertaking an entrepreneurial career is given by the creation of spin-offs (e.g. Qian 2018). In this regard, the literature acknowledges that geographical proximity plays a central role in spin-off localisation, due to local network assets (Dahl and Sorenson 2012; Qian 2018). Spin-offs are firms founded by an individual who leaves an organisation—either private or public—to create a new firm in which he/she exploits (at least part of) the knowledge—both codified and tacit[1]—developed within the previous parent organisation. Most spin-offs tend to locate very close to the parent firm or university, at least in the early phases of their development when interactions with the parent organisation are often very important for the initial growth of the firm (Buestorf and Klepper 2009; Rizzo 2015). The newly founded firm is not only dependent on the parent organisation in terms of technical knowledge but also in terms of networks, which require close proximity to be acquired and exploited (Bagley 2019). These studies indicate that new spin-off firms require positioning close to the parent organisation

[1] Despite spin-offs often exploit an intellectual property right, the successful transfer of the codified and proprietary knowledge cannot be disentangled from the transfer of more tacit components (e.g. Karnani 2013). Moreover, in Italy, academic spin-offs most often exploit only tacit competences developed in academia, without any intellectual property right (see e.g. Netval 2016; Ramaciotti and Rizzo 2015).

in order to facilitate their formation and development. Albeit some knowledge and capabilities may come from market-based channels, it seems that some knowledge features such as networks and capabilities acquired from the parent organisation may be appropriated only close to their sources, by means of non-market-based interactions. The process of new venture creation could therefore be the output of both market-based and non-market-based knowledge acquisitions by the entrepreneur or team of founders, or a combination of the two. However, when innovative capabilities must be exploited in the new venture, non-market-based knowledge flows assume a fundamental role (Zucker et al. 1998a; Karnani 2013).

Further support for the KSTE *localisation hypothesis* can be derived from the literature on agglomeration economies, acknowledged to play an important role in job creation, despite heterogeneous across different economic activities (e.g. Greenstone et al. 2010). Partly due to the circulation of free but spatially constrained knowledge spillovers (Marshall 1920), agglomeration externalities tend to operate at small-scale regional levels (Arbia 2001), as demonstrated by recent studies that investigate these using between-organisation distance-based measures (e.g. Cainelli and Ganau 2018, Coll-Martinez et al. 2019). However, the literature has substantially overlooked the quantification of the distance at which externalities manifest themselves, and this is due to the heterogeneity of geographical levels at which agglomeration is measured (Wennberg and Lindqvist 2010). Rosenthal and Strange (2001) show that knowledge spillovers have an impact on agglomeration economies only at the ZIP code level and that there is no effect at higher levels of aggregation such as the county or state. In the context of Italian manufacturing firms, Cainelli and Lupi (2010) find that the positive effect of localisation economies takes place only within two kilometres of the agglomeration externality source. Anselin et al. (1997) carry out an analysis at the US metropolitan statistical area level and observe that the impact of university knowledge on high-technology innovation is spatially constrained to a 50–70 miles distance. Sinthoven et al. (2020) find that the size of research contracts reaches a minimum at around 16 km of distance between the firm and the university but is higher at both closer and longer distances. Given the higher amount of tacit content in agglomeration externalities in the creative industries, Coll-Martinez (2019), focusing on the city of Barcelona, finds that localisation economies in this sector are present only within rings of 250 m.

The extant literature on the geographical distance at which knowledge spillovers are conducive to new venture creation is rather scarce. A few studies contribute to this debate, however. The seminal work by Rosenthal and Strange (2003) provides evidence that the effect of agglomeration externalities on firm entry and size at entry attenuates rapidly with distance and decreases sharply only a few miles beyond the focal ZIP code. For what concerns the KSTE literature, a few studies explore the relationship between knowledge endowments and entrepreneurship at a small regional scale. In an analysis at the travel-to-work-area (TTWA) level, Lasch et al. (2013) show that new information and communication technology (ICT) firms tend to locate close to ICT incumbents and identify the presence of knowledge spillovers from both public and private R&D labs. Other works show that knowledge spillovers arise also from university research. At the NUTS 3 regional level, Bonaccorsi et al. (2013) observe a positive effect of knowledge spillovers on entrepreneurial activities in Italian provinces, which is corroborated by similar findings obtained by Fritsch and Aamoucke (2013) in German districts. Audretsch and Lehmann (2005) show that higher levels of university output and regional knowledge endowments are associated with higher numbers initial public offerings for new firms located within 1.5 km of the university. Moreover, Lee et al. (2013) exploit data on small Korean regions and suggest that the effect of regional knowledge spillovers on firm entry rates is higher in intra- than inter-regions. Finally, Knoben et al. (2011) focus on Dutch municipalities and find a positive—though weak—correlation between knowledge investment and the share of entry employment in the municipality.

However, none of these works take into consideration distance-based measures of knowledge spillover, and very few account for the size at entry of new ventures, which would allow accounting for the potential success and growth of entrants. The available studies on the quantification of the distances at which knowledge spillover exerts its benefits have not reached conclusive findings. Moreover, these studies also do not account for the presence of non-linearities in the relationship between spatial spillovers and entrepreneurship. Our paper seeks to fill this gap and tests the following hypotheses:

H1. The size at entry of new firms is positively associated with knowledge spillovers at close distances to the R&D source.

H2. The positive benefit of knowledge spillovers on size at entry dissipates as the distance from the source of knowledge increases.

3 Empirical framework

The empirical analysis relies on two main sources of data. First, we use data from the ASIA database (‘Registro Statistico delle Imprese Attive’) maintained by ISTAT (Italian National Statistical Office), which provides information on the population of firms by local units. We focus on firms located in the Emilia-Romagna region, which is one of the leading regions in both Italy and in Europe in terms of GDP, innovation indicators, and governance quality (MSE 2009; European Commission 2014; Rodríguez-Pose and Garcilazo 2015). Emilia-Romagna has been investigated in the economics and management literature as a self-contained unit (Bianchi and Giordani 1993; Putnam 1993; Marzucchi et al. 2015; Ramaciotti et al. 2017): it has a population of 4.5 million (Norway, Finland, and Denmark each count just over 5 million inhabitants) and is split into 334 municipalities.

For each Emilia-Romagna firm in the ASIA data, we collected the year of firm constitution and local unit addresses, the number of employees, full-digit NACE codes, and firm legal status. We also obtained balance sheet information from the Bureau van Dijk AIDA dataset. This allows us to use R&D expenditure to build our key independent variables.[2] The advantage of these databases is that they provide firm address

[2] The R&D expenditures obtained from AIDA cannot be considered to represent the overall amount of private R&D in the region as AIDA only provides information on limited companies and disclosing R&D expenditure in balance sheets is not mandatory under Italian law. The comparison between our

information, which allows us to geolocate the firms using the Google Maps application programming interface (API) to retrieve their geographical coordinates and project them on a map. Using geolocalised firms as our unit of analysis allows us to investigate the following relationship:

$$EmpEntry_{imt} = \beta KnowledgeStock_{ig(i)t-1} + \varphi \boldsymbol{X}_{mt-1} + \delta_m + \tau_t + \varepsilon_{imt}$$

where *EmpEntry* is our measure of entrepreneurship for firm i in municipality m at time t. $\boldsymbol{X}$ is a vector of control variables, namely agglomeration economies, average income, share of employment in the financial sector, and population. τ_t captures common yearly shocks that affect the region (e.g. changes to Italian legislation that affect firm creation procedures, etc.). δ_m are municipality dummies that account for unobservable heterogeneity that is constant over time but varies across geographical areas (e.g. universities or research centres, etc.). The aim is to capture common features that characterise the environment in which the firm conducts its activities, such as the transport infrastructure. ε is the error term.

The dependent variable (*EmpEntry*) is measured as employment in the first year after constitution. Construction of this variable involved two issues. The first is related to the dataset time span. Although we are only able to observe the number of employees based on ASIA Emilia-Romagna data for the 2007–2014 period, the firm may have been founded before 2007. We, therefore, restricted our sample to focus on firms founded after 2006. The second issue is related to the year we measure employment levels. Firms may enter in one year and start their activities (i.e. appear in ASIA data) in the same or a subsequent year. In most cases, firms start their activities in their year of birth (57%), the remainder starting activities in the following year (36%) or two years later (4%). The remaining 3% start their activities between three and seven years after birth.

To obtain a sample of comparable firms, we exclude this 3% of firms and measure the size of firms in the first year available after constitution. Specifically, if the year of birth is the same as the year of entry in the ASIA data, we measure employment in the year following firm constitution. This provides a homogeneous sample of entrants. Finally, we distinguish between high- and low-tech and manufacturing and service firms using the Eurostat Glossary[3] classification of sectors.

KnowledgeStock is the main explanatory variable and is measured as the stock of R&D expenditure (per 10 million euros) available in the firm's geographical location *i*. *g(i)* is the mapping from firm *i* to an aggregate circle, defined for different radii. Following the standard economic geography approach (see, for example, Rosenthal and Strange 2003; Lens and Meltzer 2016), we use the geographical

Footnote 2 (Continued)

measure of R&D expenditure and the one provided by Eurostat indicates a very similar trend (see Fig. 3 in the Appendix); however, the amount of private R&D is slightly below the canonical two thirds of total R&D expenditure. This is mostly due to the lack of information about smaller companies in AIDA and some missing information in AIDA balance sheets. Overall, assuming these missing data to be allocated at random, we can rely on this measure for our research purposes (see e.g. Marin 2014; Ferragina et al. 2014; Bellucci et al., 2018).

[3] https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech

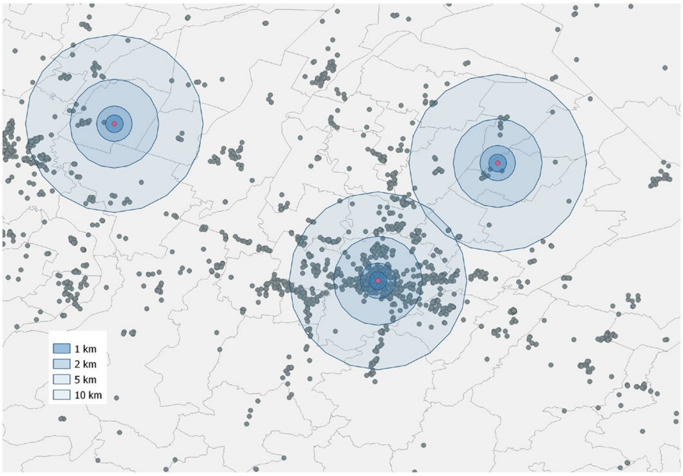


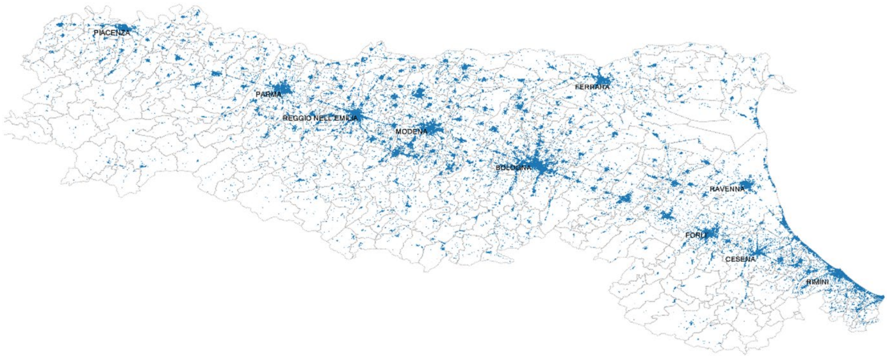
Fig. 1 Examples of neighbouring areas identified using concentric rings of 1, 2, 5 and 10 kms

coordinates for each firm as the centroid of concentric rings defined at different radii (i.e. 1, 2, 5, and 10 km) (see Fig. 1). The AIDA data allow us to identify firms with R&D activities within each ring and sum their R&D expenditure and construct the circle of knowledge stock, using a depreciation rate of 15% (Hall et al. 2005). Finally, we assign this value to the focal firm used as the centroid. It should be noted that the R&D expenditure of a firm located in a specific ring is not included in the larger (or smaller) circles. This avoids the double counting of the same R&D activities across different rings around the focal firm and ensures independence across circles defined at different radii.

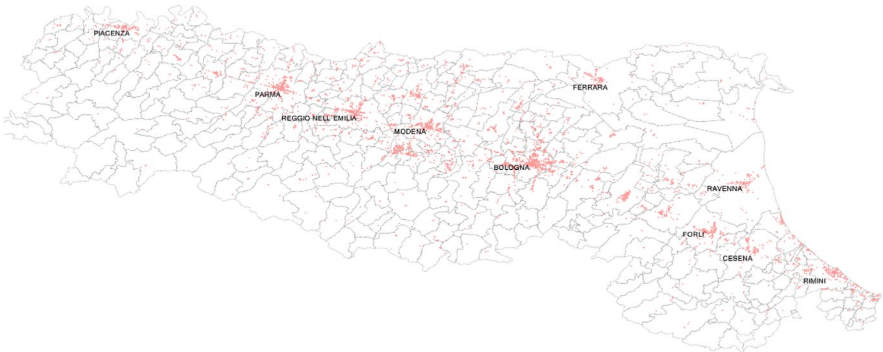
In the case of the municipality-level control variables, we rely on measures of agglomeration economy, computed as the number of employees per km^2 in municipality *i* in year *t-1* (Glaeser et al. 1992), population, income, and the share of employees working in the banking and finance sector (Aghion et al. 2019). Population and income proxy the size and wealth of a municipality, while the number of employees in the finance sector controls for the availability and ease of credit access, an important factor related to both the decision of entry and firm growth (Chodorow-Reich 2014).

4 Results

Panel A in Fig. 2 shows that firm entry is unevenly distributed across the Emilia-Romagna territory, with a marked concentration close to provincial capitals. In addition, with the exceptions of Ferrara and Ravenna, most firms are located along the A1 and A14 highways, which cross the region from the West (Piacenza) to the Southeast (Rimini). We find a similar geographical distribution based on the geolocalisation of firms retrieved from AIDA that are involved in R&D activities (panel B in Fig. 2). As



Panel A



Panel B

Fig. 2 Geographical distribution of entrant firms over the 2007–2014 period (panel A) and firms that carry out R&D activities (panel B)

expected, only a small number of firms invest in R&D, and these are mostly located close to Bologna, Modena, Reggio nell'Emilia, and Parma.

From a sectoral perspective, the trends in Tables 1 and 2 show how labour market dynamics related to entrepreneurship have evolved in the Emilia-Romagna region.[4] They show that with the exception of medium–low-tech manufacturing, which increased by 4.26% between 2009 and 2014, the average size at entry in all sectors has generally decreased over time. However, total employment at entry has also decreased in almost all sectors, with the exception of high-tech manufacturing and low-tech services (+12.75% and +8.9%, respectively). Overall, these descriptive statistics provide evidence of a reduction in firm size over time, which needs to be considered in policy frameworks.

Table 3 presents descriptive statistics for our variables, whereas Tables 4 and 5 report the results of our estimates. The dependent variable, that is, the

[4] The sectors included in the tables are based on the Eurostat Glossary classification; high-tech sectors include high- and medium–high-tech industries.

Table 1 Trends in average entry size by sector (2009–2014)

	Sector	2009	2012	2014	% Change 2009–2014
Manufacturing	High tech	2.50	2.79	1.99	− 20.13
Manufacturing	Low tech	3.61	3.10	3.22	− 10.62
Manufacturing	Medium–high tech	3.73	2.79	3.50	− 6.00
Manufacturing	Medium–low tech	2.99	2.98	3.11	4.26
Services	High tech	1.80	1.69	1.68	− 6.84
Services	Low tech	1.94	1.93	1.93	− 0.34
	Others	1.55	1.55	1.53	− 1.61

Table 2 Trends in total employment at entry by sector (2009–2014)

	Sector	2009	2012	2014	% Change 2009–2014
Manufacturing	High tech	42.4	58.5	47.8	12.75
Manufacturing	Low tech	2,592.4	2,425.7	2,342.9	− 9.62
Manufacturing	Medium–high tech	779.0	477.0	623.6	− 19.95
Manufacturing	Medium–low tech	1,926.0	1,551.6	1,503.7	− 21.93
Services	High tech	2,183.6	1,751.8	1,841.5	− 15.66
Services	Low tech	10,859.1	10,530.6	11,825.4	8.90
	Others	5,185.2	3,659.8	3,329.6	− 35.79
Total		23,567.7	20,455.0	21,514.6	− 8.71

full-time equivalent number of employees at entry, is logarithm-transformed. Table 4 expresses the main independent variables—the knowledge stock variables—in levels, that is, in millions of euros. The R&D stock variables are log-transformed in Table 5, which enables us to calculate elasticities, at the expense of excluding those rings that include firms not engaged in R&D. Transforming the stock variables into logarithm form also normalises their distribution.

Tables 4 and 5 report the results for the different samples. In both tables, column (1) refers to the full sample, columns (2) and (3) compare high- and low-tech sectors, columns (4) and (5) report the respective results for the services and manufacturing sectors, and columns (6) and (7) report the results for the high-tech sector, distinguishing between high-tech services and high-tech manufacturing. The main finding in column (1) in both tables is the positive and significant coefficient of knowledge stock within 1 km radius of the firm's location (address at entry) and the absence of a significant association in the more distant circles. It must be noted that while the coefficient in the second ring remains positive (albeit non-significant), the coefficients in the third and fourth rings become negative, although not statistically different from 0. When exploring the relationship in the different samples, we observe that the pattern for the first two rings is exactly the same for all samples

Table 3 Descriptive statistics

Variables	Variable description	Obs	Mean	Std. Dev	Min	Max
EmpEntry	# of employees in the first year after firm creation	65,203	1.99	2.342	0.01	38.89
KnowledgeStock 1 km	Knowledge stock within a 1 km radius (per 10 million €)	65,203	0.22	0.941	0	20.095
KnowledgeStock 2 km	Knowledge stock from a 1 to 2 km radius (per 10 million €)	65,203	0.48	1.642	0	18.685
KnowledgeStock 5 km	Knowledge stock from a 2 to 5 km radius (per 10 million €)	65,203	1.87	3.723	0	43.318
KnowledgeStock 10 km	Knowledge stock from a 5 to 10 km radius (per 10 million €)	65,203	3.52	5.471	0	44.63
EmpDens	Employment density	65,203	293.01	323.15	0.58	1,296
Population	Number of inhabitants	65,203	95,280	110,360	152	380,635
Income	Average income	65,203	23,046	2,961	9,719	29,665
Finance	Employment share of the financial sector	65,203	0.024	0.013	0	0.08

Table 4 OLS regression (log-level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Full sample	High-tech	Low-tech	Services	Manufacturing	High-tech manufacturing	High-tech services
K_Stock 1 km	0.00974***	0.01922***	0.00933**	0.00926**	0.02331**	0.01947	0.02059***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.011)	(0.035)	(0.007)
K_Stock 2 km	0.00335	0.00881	0.00222	0.00419	−0.00207	0.01719	0.00905
	(0.002)	(0.006)	(0.003)	(0.002)	(0.009)	(0.028)	(0.006)
K_Stock 5 km	−0.00279	0.00160	−0.00371	−0.00372**	−0.00052	−0.02068	0.00422
	(0.001)	(0.003)	(0.002)	(0.002)	(0.005)	(0.011)	(0.004)
K_Stock 10 km	−0.00050	−0.00159	−0.00058	−0.00020	−0.00537	0.01559	−0.00418**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.008)	(0.002)
EmpDens	−0.00038	−0.00066	−0.00035	−0.00066**	0.00113	0.00087	−0.00080
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)
Income	0.23096	−0.83567	0.51008**	0.18250	1.58480**	−1.53985	−0.95501
	(0.191)	(0.639)	(0.242)	(0.229)	(0.681)	(2.629)	(0.623)
Population	−0.02005	0.10462	−0.07031	−0.12177	0.98052	1.86413	0.46609
	(0.224)	(0.732)	(0.296)	(0.273)	(0.781)	(2.546)	(0.689)
Finance	0.01519	−0.01049	0.00971	0.01987	0.01167	−0.21589	0.01883
	(0.023)	(0.073)	(0.030)	(0.028)	(0.074)	(0.275)	(0.067)
Municipality dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Observations	65,023	8,506	41,377	41,193	8,690	1,157	7,349
R-squared	0.014	0.057	0.019	0.015	0.067	0.258	0.058

The full sample also includes construction sector, which is not included in the other samples

Robust standard errors are in parentheses;

***$p < 0.01$, ** $p < 0.05$

Table 5 OLS regression (log–log)—Radii with R&D greater than zero

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Full sample	High-tech	Low-tech	Services	Manufacturing	High-tech manufacturing	High-tech services
K_Stock 1 km	0.01381***	0.02240***	0.01200***	0.00788***	0.03030***	0.05985***	0.01439***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.006)	(0.019)	(0.004)
K_Stock 2 km	−0.00779***	−0.00035	−0.00870***	−0.00491**	−0.00183	0.00340	0.00274
	(0.002)	(0.005)	(0.003)	(0.002)	(0.008)	(0.022)	(0.005)
K_Stock 5 km	−0.01746***	−0.00555	−0.02268***	−0.01826***	−0.01772	−0.06160	0.00274
	(0.004)	(0.010)	(0.005)	(0.005)	(0.013)	(0.037)	(0.009)
K_Stock 10 km	0.01553***	−0.00808	0.01888***	0.00926	0.01946	0.07492	−0.01804
	(0.005)	(0.013)	(0.007)	(0.006)	(0.020)	(0.053)	(0.013)
EmpDens	−0.00048	−0.00150**	−0.00022	−0.00062**	0.00099	−0.00304	−0.00123
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)
Income	0.18244	−1.52033	0.70515**	0.26540	0.57941	−5.65067	−1.18140
	(0.281)	(0.822)	(0.350)	(0.323)	(0.993)	(3.275)	(0.818)
Population	−0.17030	1.22600	−0.37484	−0.24109	1.10451	4.11066	1.35968
	(0.355)	(0.919)	(0.453)	(0.417)	(1.195)	(3.269)	(0.939)
Finance	0.03285	−0.01809	0.05433	0.07161	−0.04112	−0.55331	0.06628
	(0.038)	(0.102)	(0.049)	(0.044)	(0.129)	(0.335)	(0.100)
Municipality dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Observations	41,396	6,127	26,939	28,004	5,062	728	5,399
R-squared	0.017	0.063	0.020	0.016	0.079	0.288	0.049

The full sample also includes construction sector, which is not included in the other samples

Robust standard errors are in parentheses;

*** $p<0.01$, ** $p<0.05$

analysed except high-tech manufacturing, which displays no relationship in the first ring. For what concerns the third ring (2–5 km), we observe a negative relationship, significant at the 5% level, only for the service sector. The last ring, which captures R&D stocks from 5 to 10 km away from the localisation of the entrants, conversely displays a negative relationship in the high-tech service sector. This indicates that in the proximity of the knowledge source we find higher sizes at entry, while as we move farther away from it the average size at entry diminishes. Overall, Table 4 highlights a general pattern: a positive and significant role of knowledge spillovers on employment at entry only for very proximate entering firms. This is in line with the seminal work by Rosenthal and Strange (2003) and indicates that knowledge spillovers dissipate rapidly as we move away from the R&D source.

In Table 5, we report the result of an ordinary least squares estimation in which the explanatory variables of interest are also log-transformed. This allows us to study the elasticity between R&D knowledge spillovers and entry employment for those areas where there is at least one firm engaged in R&D activity close to the entrants, and also to normalise the skewed stock variables. The results are in line with those reported in Table 4, although some differences emerge for what concerns the larger rings. On the one hand, we observe that the patterns in the first, second, and third rings are consistent with Table 4. More specifically, the coefficient of R&D stock in the first ring is positive and significant for all samples analysed—including the high-tech manufacturing sector, which was not significant in Table 4. Column (1) in Table 5 shows that a 10% increase in the knowledge stock in the first ring increases entry firm employment by 1.4% in the full sample, while in the case of high-tech manufacturing a 10% increase in the knowledge stock in the first ring increases size at entry by almost 6%.[5] Similarly to Table 4, the second and third rings show a negative or a non-significant coefficient, indicating that as we move away from the source of the R&D knowledge spillover, the average size at entry diminishes. The fourth ring, measuring knowledge spillovers at 5 to 10 km from the entry, conversely shows a positive and significant coefficient in the full and in the low-tech sample. Considering that the low-tech sample is one of the biggest samples and that in all other samples the coefficient of this variable is non-significant, we can argue that this non-linear relationship is observed only for low-tech entry. This result is in line with our argument that the most innovative firms that require proximity, benefit from unexploited knowledge spillovers when entering the market. Firms in high-tech sectors exploiting the knowledge spillovers coming from private R&D activities have, on average, a larger size the closer they are to the source of R&D activity. Conversely, larger low-tech firms entering the market in response to the presence of knowledge spillovers do it either very close to or far away

[5] It must be noted that our model is able to explain only a small portion of the total variance, and most of this variance is explained, as could be expected, by municipality fixed effects. With reference to column (1) of Table 4, the effect size of the whole model is 5%, while the partial η^2 effect size for the first ring is 0.2%; conversely the confidence interval for all other rings include the null value of zero. With reference to column (6) of Table 4 the total variance explained raise to 29%, where the partial η^2 is 22% for municipalities dummy variables and almost 2% for our first ring, this being again the only ring where the confidence interval does not cross the null value of zero. Results in Table 5 display similar total and partial effect size.

from the sources of the spillover. Therefore, we detect some sort of non-linearities for entry, but only for less-innovative entries.

Overall, we can state that our hypothesis H1 is supported as the size at entry is greater closer to the source of knowledge spillovers. Hypothesis H2 is supported for all sectors except the low-tech sectors, for which we observe that greater size characterises entrant firms either very close to or far away from the source of knowledge. These results highlight the differences between spillover receivers: more innovative firms require, on average, being at a closer distance to benefit from spillovers compared to less innovative firms (see also Cruz and Teixeira 2015).

4.1 Robustness checks

In order to support our results, we conduct a number of robustness checks, the results of which are reported in the Appendix. First of all, we replicate the estimates in Table 4 by retaining the dependent variable as a count variable and employing Poisson estimation with robust standard errors. Table 6 in the Appendix reports the results of this estimation, showing similar output to Table 4. The coefficients of the first ring are all positive but significant only for the full high-tech and high-tech services samples. The third and fourth rings show only non-significant negative coefficients, but the high-tech manufacturing sector has a negative and significant coefficient.

In Table 7 in the Appendix, we estimate a series of OLS regressions without log-transforming our explanatory variables and in which we only consider those rings for which there is a positive R&D expenditure. In other words, we replicate the estimates of Table 4 for the sample of Table 5: by not log-transforming our R&D stock, we avoid eventual reduction in the size of expenditure in the different rings due to the transformation. Results show positive and significant coefficients only for the first ring, but for the high-tech manufacturing sector sample there is an absence of association in the first ring and a negative association in the third ring. Finally, Table 8 replicates Table 7 without log-transforming the dependent variable and employing a Poisson estimation. Results are again very similar, showing the presence of positive association between R&D spillovers and entry size only in very close proximity to the spillovers.

5 Conclusions

The present paper investigated the spatial contingencies at the heart of the relationship between knowledge spillovers and entrepreneurship and contributes to the extant literature in two ways. First, by exploring the geography of R&D knowledge externalities it provides empirical support for the *localisation hypothesis*, which is one of the foundations of the KSTE. We quantified the distance at which entrepreneurial activities are more likely to benefit from knowledge spillovers and, in particular, the distance at which this association dissipates. In so doing our findings also contribute to the literature stressing the importance of regional absorptive capacity, by showing that this can be very heterogeneous within regions. Second, we show that entrants are heterogeneous in terms their ability to grasp knowledge spillovers and the quality of their entrepreneurial activities. That is, we distinguished between groups of firms by sector and employment at entry—a measure of entrepreneurship that proxies job creation. Our empirical exercise is in line with the few studies that use entry size to measure the quality of entrepreneurial activity (see, for example, Calvino et al. 2016).

The results show that the relationship between the level of R&D stock and entry size is positive in the proximity (i.e. within 1 km) of entry firm locations. This relationship weakens as distance increases and is not statistically significant at a 2 km distance between the entrant firm's geographical coordinates and the location of the R&D investment. At distances of 2–5 km, the association is sometimes negative, indicating that the size at entry diminishes when moving farther away from the source of the spillover. We also detect some non-linearities in this association; however, these only characterise the low-tech sectors: for less innovative firms we find the size at entry to be associated with knowledge spillover either within 1 km or more than 5 km away from the source of the spillover. Non-linearities are not detected for more innovative sectors, indicating that larger, more innovative firms seeking to exploit spillover from private R&D activities tend to enter the market very close to the sources of this knowledge.

Our findings add to the insights of Rosenthal and Strange (2003; 2005) regarding the association between knowledge spillovers generated by agglomeration economies and entry rates and employment at entry. Rosenthal and Strange (2003) found that agglomeration economies increase entrepreneurship only at short distances from the agglomeration sources and that this positive effect decreases rapidly after 2 miles. Our results support Rosenthal and Strange's (2003, pp. 387–388) argument that 'information spillovers that require frequent contact between workers may dissipate over a short distance as walking to a meeting place becomes difficult or as random encounters become rare'.

Our study is not exempt from limitations. First, we consider only knowledge spillovers from R&D activity conducted by private companies, and we do not include R&D conducted by universities and public research centres. However, since private firm R&D tends to be applied research that is close to the market, we believe that this is a minor limitation. In other words, private R&D knowledge spillovers are more likely to be commercialisable compared to spillovers from university R&D. Moreover, our focus on private R&D expenditure allows us to confirm the findings of most KSTE studies that rely on university knowledge spillovers; it is also worth noting that private company R&D investments represent the largest proportion of R&D expenditure. Another limitation is related to the source of our R&D expenditure data: in Italy, balance sheet information includes advertising expenditure. This is a major limitation, however balance sheet information is widely used to proxy private R&D expenditure in empirical studies (e.g. Marin 2014; Ferragina et al. 2014; Bellucci et al., 2018). The third limitation is that the control variables were collected at the municipality rather than the radius level: in our datasets, firm geolocalisation is available only for entrants and R&D-performing firms. Further analysis is required to include control variables at a fine-grained geographical level.

Such further research could also better detect effect size of our estimates, that at the present form remain small and mostly captured by municipality-fixed effects.

This work provides evidence that innovative entrepreneurship of a greater size based on uncommercialised knowledge is associated with firms that are close to the knowledge source. Conversely, it seems that larger low-tech entrepreneurship can emerge either very close to or far away from the source of the spillover. Further research is needed to understand the mechanisms that drive these spatial patterns (Breschi and Lissoni 2001). Policies aimed at increasing entrepreneurial activity, and especially innovative ones—an issue that in Europe is mostly a matter of NUTS 2 regional government (see, for example, Ramaciotti et al. 2017)—could benefit from our findings. More specifically, our results indicate that R&D expenditure generates important spillovers for (successful) entrepreneurial activity, especially but not limited to, high tech entrepreneurship. Local development policies that provide incentives for (private) R&D activities would obtain indirect positive benefits in terms of entrepreneurship, and specifically on high-entry size entrepreneurship, with a premium for high-tech sectors.

Appendix

See Fig. 3 and Tables 6, 7 and 8

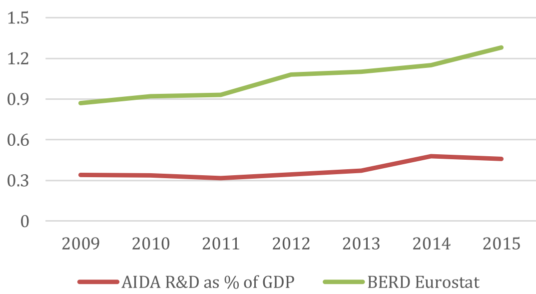


Fig. 3 Comparison between the AIDA amount of R&D expenditure as a percentage of GDP and the Eurostat value of the Business Enterprise R&D expenditure as a percentage of GDP (BERD). Region Emilia-Romagna, 2009–2015

Table 6 Poisson regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Full sample	High-tech	Low-tech	Services	Manufacturing	High-tech manufacturing	High-tech services
K_Stock 1 km	0.01238***	0.02453**	0.01027	0.01066	0.02284	0.03049	0.02569**
	(0.005)	(0.010)	(0.006)	(0.006)	(0.013)	(0.037)	(0.011)
K_Stock 2 km	0.00535	0.01676	0.00343	0.00751	−0.00177	0.03828	0.01741
	(0.004)	(0.010)	(0.004)	(0.004)	(0.012)	(0.030)	(0.011)
K_Stock 5 km	−0.00300	0.00487	−0.00493	−0.00294	−0.00710	−0.03415**	0.01262
	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)	(0.014)	(0.007)
K_Stock 10 km	−0.00053	−0.00258	−0.00087	0.00007	−0.00561	0.01394	−0.00648
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.010)	(0.004)
EmpDens	−0.00039	−0.00082	−0.00039	−0.00072	0.00126	0.00083	−0.00071
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Income	0.41879	−1.99512	0.84209	0.33957	1.31976	−2.13441	−2.51680**
	(0.361)	(1.030)	(0.455)	(0.471)	(0.812)	(2.818)	(1.006)
Population	0.08193	0.00574	0.19656	−0.21100	1.93297	2.08643	0.19847
	(0.397)	(1.352)	(0.502)	(0.480)	(1.028)	(3.231)	(1.266)
Finance	0.02629	−0.03881	0.04045	0.07883	−0.02263	−0.35779	0.06621
	(0.040)	(0.124)	(0.049)	(0.047)	(0.091)	(0.304)	(0.120)
Municipality dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Observations	65,023	8,506	41,377	41,193	8,690	1,157	7,349

The full sample also includes construction sector, which is not included in the other samples

Robust standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$

Table 7 OLS regression using radii with R&D greater than zero

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Full sample	High-tech	Low-tech	Services	Manufacturing	High-tech manufacturing	High-tech services
K_Stock 1 km	0.00976***	0.02008**	0.01035**	0.00971**	0.03638**	0.05716	0.02030**
	(0.003)	(0.008)	(0.004)	(0.004)	(0.016)	(0.053)	(0.008)
K_Stock 2 km	0.00273	0.00840	0.00228	0.00414	−0.00093	0.01240	0.00968
	(0.002)	(0.006)	(0.003)	(0.003)	(0.010)	(0.030)	(0.006)
K_Stock 5 km	−0.00358**	0.00172	−0.00393	−0.00354	−0.00081	−0.02442	0.00574
	(0.002)	(0.004)	(0.002)	(0.002)	(0.007)	(0.014)	(0.004)
K_Stock 10 km	−0.00114	−0.00233	−0.00129	−0.00106	−0.00460	0.01178	−0.00375
	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)	(0.011)	(0.003)
EmpDens	−0.00070**	−0.00141	−0.00048	−0.00081**	0.00076	−0.00268	−0.00098
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)
Income	0.20235	−1.44219	0.73014**	0.30199	0.53188	−4.75613	−1.09555
	(0.283)	(0.825)	(0.352)	(0.325)	(1.007)	(3.346)	(0.818)
Population	−0.09802	1.22024	−0.29790	−0.19399	1.20629	3.37100	1.39293
	(0.357)	(0.928)	(0.456)	(0.420)	(1.209)	(3.366)	(0.946)
Finance	0.02819	0.00020	0.05029	0.06784	−0.05153	−0.52797	0.10050
	(0.039)	(0.106)	(0.050)	(0.045)	(0.131)	(0.337)	(0.103)
Municipality dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Observations	41,396	6,127	26,939	28,004	5,062	728	5,399
R-squared	0.015	0.060	0.018	0.015	0.075	0.278	0.048

The full sample also includes construction sector, which is not included in the other samples

Robust standard errors are in parentheses;

*** $p<0.01$, ** $p<0.05$

Table 8 Poisson regression using radii with R&D greater than zero

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Full sample	High-tech	Low-tech	Services	Manufacturing	High-tech manufacturing	High-tech services
K_Stock 1 km	0.01188**	0.02633**	0.01243	0.01229	0.03403	0.08538	0.02758**
	(0.005)	(0.012)	(0.007)	(0.006)	(0.018)	(0.049)	(0.013)
K_Stock 2 km	0.00373	0.01708	0.00275	0.00707	−0.00177	0.03608	0.01930
	(0.004)	(0.011)	(0.005)	(0.004)	(0.013)	(0.033)	(0.012)
K_Stock 5 km	−0.00471	0.00660	−0.00580	−0.00269	−0.00861	−0.04295***	0.01649**
	(0.003)	(0.007)	(0.004)	(0.003)	(0.008)	(0.015)	(0.008)
K_Stock 10 km	−0.00158	−0.00399	−0.00186	−0.00168	−0.00390	0.01026	−0.00619
	(0.002)	(0.005)	(0.002)	(0.002)	(0.006)	(0.012)	(0.005)
EmpDens	−0.00097	−0.00169	−0.00074	−0.00105	0.00073	−0.00152	−0.00095
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
Income	0.66312	−3.27168**	1.64821***	0.94171	0.21736	−6.51886	−2.79136
	(0.464)	(1.353)	(0.550)	(0.547)	(1.159)	(3.639)	(1.434)
Population	0.02478	1.92081	−0.15204	−0.36592	2.48259	4.44234	1.82059
	(0.610)	(1.632)	(0.746)	(0.719)	(1.566)	(4.123)	(1.761)
Finance	0.06065	−0.00704	0.12535	0.17977**	−0.14862	−0.68845	0.26241
	(0.063)	(0.177)	(0.077)	(0.073)	(0.155)	(0.359)	(0.172)
Municipality dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Observations	41,396	6,127	26,939	28,004	5,062	728	5,399

The full sample also includes construction sector, which is not included in the other samples

Robust standard errors are in parentheses;

*** $p < 0.01$, ** $p < 0.05$

Funding Open access funding provided by Università degli Studi di Ferrara within the CRUI-CARE Agreement.

References

Abreu M (2011) Absorptive capacity in a regional context. In: Cooke P et al (eds) Handbook of regional innovation and growth. Edgar Elgar, United Kingdom

Acs ZL, Braunerhjelm P, Audretsch DB, Carlsson B (2009) The knowledge spillover theory of entrepreneurship. Small Bus Econ 32:15–30. https://doi.org/10.1007/s11187-008-9157-3

Aghion P, Akcigit U, Bergeaud A, Blundell R, Hémous D (2019) Innovation and top income inequality. Rev Econ Stud 86(1):1–45. https://doi.org/10.1093/restud/rdy027

Anselin L, Varga A, Acs ZJ (1997) Local geographic spillovers between university research and high technology innovations. J Urban Econ 42(3):422–448. https://doi.org/10.1006/juec.1997.2032

Armington C, Acs ZJ (2002) The determinants of regional variation in new firm formation. Reg Stud 36(1):33–45. https://doi.org/10.1080/00343400120099843

Arbia G (2001) Modelling the geography of economic activities on a continuous space. Pap Reg Sci 80(4):411–424. https://doi.org/10.1007/PL00013646

Asheim BT, Boschma R, Cooke P (2011) Constructing regional advantage: platform policies based on related variety and differentiated knowledge bases. Reg Stud 45(7):893–904. https://doi.org/10.1080/00343404.2010.543126

Åstebro T, Thompson P (2011) Entrepreneurs, jacks of all trades or hobos? Res Policy 40(5):637–649. https://doi.org/10.1016/j.respol.2011.01.010

Audretsch B (1998) Agglomeration and the location of innovative activity. Oxf Rev Econ Policy 14(2):18–29. https://doi.org/10.1093/oxrep/14.2.18

Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. Am Econ Rev 86(3):630–640

Audretsch DB, Keilbach MC, Lehmann EE (2006) Entrepreneurship and economic growth. Oxford University Press, Oxford

Audretsch DB, Keilbach M (2007) The theory of knowledge spillover entrepreneurship. J Manage Stud 44:1242–1254. https://doi.org/10.1111/j.1467-6486.2007.00722.x

Audretsch DB, Lehmann EE (2005) Does the knowledge spillover theory of entrepreneurship hold for regions? Res Policy 34(8):1191–1202. https://doi.org/10.1016/j.respol.2005.03.012

Bagley MJ (2019) Networks, geography and the survival of the firm. J Evol Econ 29(4):1173–1209. https://doi.org/10.1007/s00191-019-00616-z

Bahar D, Hausmann R, Hidalgo CA (2014) Neighbors and the evolution of the comparative advantage of nations: evidence of international knowledge diffusion? J Int Econ 92:111–123. https://doi.org/10.1016/j.jinteco.2013.11.001

Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. Prog Hum Geogr 28(1):31–56. https://doi.org/10.1191/0309132504ph469oa

Bellucci A, Pennacchio L, Zazzaro A (2019) Public R&D subsidies: collaborative versus individual place-based programs for SMEs. Small Bus Econ 52(1):213–240. https://doi.org/10.1007/s11187-018-0017-5

Berchicci L, de Jong JP, Freel M (2016) Remote collaboration and innovative performance: the moderating role of R&D intensity. Ind Corp Chang 25(3):429–446. https://doi.org/10.1093/icc/dtv031

Bianchi P, Giordani M (1993) Innovation policy at the local and national levels: the case of Emilia-Romagna. Eur Plan Stud 1(1):25–41. https://doi.org/10.1080/09654319308720193

Bonaccorsi A, Colombo MG, Guerini M, Rossi-Lamastra C (2013) University specialization and new firm creation across industries. Small Bus Econ 41(4):837–863. https://doi.org/10.1007/s11187-013-9509-5
Boyer T, Blazy R (2014) Born to be alive? The survival of innovative and non-innovative French micro-start-ups. Small Bus Econ 42(4):669–683. https://doi.org/10.1007/s11187-013-9522-8
Breschi S, Lissoni F (2001) Knowledge spillovers and local innovation systems: a critical survey. Ind Corp Chang 10:975–1005. https://doi.org/10.1093/icc/10.4.975
Breschi S, Lissoni F (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. J Econ Geogr 9(4):439–468. https://doi.org/10.1093/jeg/lbp008
Broström A (2010) Working with distant researchers—Distance and content in university–industry interaction. Res Policy 39(10):1311–1320. https://doi.org/10.1016/j.respol.2010.09.002
Buenstorf G, Klepper S (2009) Heritage and agglomeration: the Akron tyre cluster revisited. Econ J 119(537):705–733. https://doi.org/10.1111/j.1468-0297.2009.02216.x
Cainelli G, Ganau R (2018) Distance-based agglomeration externalities and neighbouring firms' characteristics. Reg Stud 52:922–933. https://doi.org/10.1080/00343404.2017.1360482
Cainelli G, Ganau R, Giunta A (2018) Spatial agglomeration, global value chains, and productivity. Micro-evidence from Italy and Spain. Econ Lett 169:43–46. https://doi.org/10.1016/j.econlet.2018.04.020
Cainelli G, Lupi C (2010) Does spatial proximity matter? Micro-evidence from Italy. In: De Liso N, Leoncini R (eds) Internationalization, technological change and the theory of the firm. Routledge, London, pp 163–186
Calvino F, Criscuolo C, Menon C (2016) No country for young firms?: start-up dynamics and national policies. OECD Science, Technology and Industry Policy Papers, No. 29, OECD Publishing: Paris
Chodorow-Reich G (2014) The employment effects of credit market disruptions: firm level evidence from the 2008–09 financial crisis. Q J Econ 129(1):1–59. https://doi.org/10.1093/qje/qjt031
Coad A, Rao R (2008) Innovation and firm growth in high-tech sectors: a quantile regression approach. Res Policy 37(4):633–648. https://doi.org/10.1016/j.respol.2008.01.003
Cohen WM, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. Adm Sci Q. https://doi.org/10.2307/2393553
Coll-Martínez E (2019) Creativity and the city: testing the attenuation of agglomeration economies in Barcelona. J Cult Econ 43(3):365–395. https://doi.org/10.1007/s10824-019-09340-9
Coll-Martínez E, Moreno-Monroy AI, Arauzo-Carod JM (2019) Agglomeration of creative industries: an intra-metropolitan analysis for Barcelona. Pap Reg Sci 98(1):409–431. https://doi.org/10.1111/pirs.12330
Criscuolo C, Gal PN, Menon C (2014) The dynamics of employment growth: new evidence from 18 countries. OECD Science, Technology and Industrial Policy Paper, No. 14, OECD Publishing: Paris
Cruz SS, Teixeira AA (2015) The neglected heterogeneity of spatial agglomeration and co-location patterns of creative employment: evidence from Portugal. Ann Reg Sci 54(1):143–177. https://doi.org/10.1007/s00168-014-0649-6
Dahl MS, Sorenson O (2012) Home sweet home: entrepreneurs' location choices and the performance of their ventures. Manage Sci 58(6):1059–1071. https://doi.org/10.1287/mnsc.1110.1476
De Jong JP, Freel M (2010) Absorptive capacity and the reach of collaboration in high technology small firms. Res Policy 39(1):47–54. https://doi.org/10.1016/j.respol.2009.10.003
Decker RA, Haltiwanger J, Jarmin RS, Miranda J (2014) The role of entrepreneurship in US job creation and economics dynamism. J Econ Perspect 28(3):3–24. https://doi.org/10.1257/jep.28.3.3
European Commission (2014). European Commission. Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs. Regional innovation scoreboard 2014. Brussels: European Commission
Feldman MP, Audretsch DB (1999) Innovation in cities: science-based diversity, specialization and localized competition. Eur Econ Rev 43(2):409–429. https://doi.org/10.1016/S0014-2921(98)00047-6
Ferragina AM, Pittiglio R, Reganati F (2014) Does multinational ownership affect firm survival in Italy? J Bus Econ Manag 15(2):335–355. https://doi.org/10.3846/16111699.2012.707622
Fritsch M, Aamoucke R (2013) Regional public research, higher education, and innovative start-ups: an empirical investigation. Small Bus Econ 41(4):865–885. https://doi.org/10.1007/s11187-013-9510-z
Fritsch M, Franke G (2004) Innovation, regional knowledge spillovers and R&D cooperation. Res Policy 33(2):245–255. https://doi.org/10.1016/S0048-7333(03)00123-9
Geroski P, Machin S (1992) Do innovating firms outperform non-innovators? Bus Strateg Rev 3(2):79–90. https://doi.org/10.1111/j.1467-8616.1992.tb00030.x
Geroski PA, Mata J, Portugal P (2010) Founding conditions and the survival of new firms. Strateg Manag J 31:510–529. https://doi.org/10.1002/smj.823

Glaeser EL, Kallal HD, Scheinkman JA, Shleifer A (1992) Growth in cities. J Polit Econ 100:1126–1152. https://doi.org/10.1086/261856

Greenstone M, Hornbeck R, Moretti E (2010) Identifying agglomeration spillovers: evidence from winners and losers of large plant openings. J Polit Econ 118(3):536–598. https://doi.org/10.1086/653714

Hall B, Jaffe A, Trajtenberg M (2005) Market value and patent citations. RAND J Econ 86:2418–2427

Harrison R, Jaumandreu J, Mairesse J, Peters B (2014) Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. Int J Ind Organ 35:29–43. https://doi.org/10.1016/j.ijindorg.2014.06.001

Howells JRL (2002) Tacit knowledge, innovation and economic geography. Urban Stud 39(5/6):871–884. https://doi.org/10.1080/00420980220128354

Karnani F (2013) The university's unknown knowledge: tacit knowledge, technology transfer and university spin-offs findings from an empirical study based on the theory of knowledge. J Technol Transf 38(3):235–250. https://doi.org/10.1007/s10961-012-9251-1

Knoben J, Ponds R, van Oort F (2011) Employment from new firm formation in the Netherlands: agglomeration economies and the knowledge spillover theory of entrepreneurship. Entrep Reg Dev 23(3–4):135–157. https://doi.org/10.1080/08985620903183736

Lasch F, Robert F, Le Roy F (2013) Regional determinants of ICT new firm formation. Small Bus Econ 40(3):671–686. https://doi.org/10.1007/s11187-011-9382-z

Lazear E (2005) Entrepreneurship. J Law Econ 23(4):649–680. https://doi.org/10.1086/491605

Lee IH, Hong E, Sun L (2013) Regional knowledge production and entrepreneurial firm creation: spatial dynamic analyses. J Bus Res 66(10):2106–2115. https://doi.org/10.1016/j.jbusres.2013.02.037

Lens MC, Meltzer R (2016) Is crime bad for business? Crime and commercial property values in New York City. J Reg Sci 56(3):442–470. https://doi.org/10.1111/jors.12254

Marin G (2014) Do eco-innovations harm productivity growth through crowding out? Results of an extended CDM model for Italy. Res Policy 43(2):301–317. https://doi.org/10.1016/j.respol.2013.10.015

Marshall A (1920) Principles of economics. Macmillan and Co, London

Marzucchi A, Antonioli D, Montresor S (2015) Industry–research co-operation within and across regional boundaries. What does innovation policy add? Pap Reg Sci 94(3):499–524. https://doi.org/10.1111/pirs.12079

Mata J, Portugal P, Guimaraes P (1995) The survival of new plants: start-up conditions and post-entry evolution. Int J Ind Organ 13(4):459–481. https://doi.org/10.1016/0167-7187(95)00500-5

Miguélez E, Moreno R (2015) Knowledge flows and the absorptive capacity of regions. Res Policy 44(4):833–848. https://doi.org/10.1016/j.respol.2015.01.016

Moretti E, Thulin P (2013) Local multipliers and human capital in the United States and Sweden. Ind Corp Chang 22(1):339–362. https://doi.org/10.1093/icc/dts051

Mowery DC, Ziedonis AA (2015) Markets versus spillovers in outflows of university research. Res Policy 44(1):50–66. https://doi.org/10.1016/j.respol.2014.07.019

MSE (2009). Migliorare le politiche di ricerca e innovazione per le regioni. Contenuti e processi di policy. Dipartimento per lo Sviluppo e la Coesione Economica. Retrieved in December 2017 from http://www.dps.tesoro.it

Netval (2016). XIII Rapporto Netval sulla valorizzazione della ricerca pubblica italiana. Ricerca, valorizzazione dei risultati ed impatto. www.netval.it

Plummer LA, Acs ZJ (2014) Localized competition in the knowledge spillover theory of entrepreneurship. J Bus Ventur 29(1):121–136. https://doi.org/10.1016/j.jbusvent.2012.10.003

Putnam R (1993) Making democracy work. Princeton University Press, Princeton

Qian H (2018) Knowledge-based regional economic development: a synthetic review of knowledge spillovers, entrepreneurship, and entrepreneurial ecosystems. Econ Dev Q 32(2):163–176. https://doi.org/10.1177/0891242418760981

Ramaciotti L, Muscio A, Rizzo U (2017) The impact of hard and soft policy measures on new technology-based firms. Reg Stud 51(4):629–642. https://doi.org/10.1080/00343404.2016.1255319

Ramaciotti L, Rizzo U (2015) The determinants of academic spin-off creation by Italian universities. R&D Manag 45(5):501–514. https://doi.org/10.1111/radm.12105

Rizzo U (2015) Why do scientists create academic spin-offs? The influence of the context. J Technol Transf 40(2):198–226. https://doi.org/10.1007/s10961-014-9334-2

Rodríguez-Pose A, Crescenzi R (2008) Mountains in a flat world: why proximity still matters for the location of economic activity. Camb J Reg Econ Soc 1(3):371–388. https://doi.org/10.1093/cjres/rsn011

Rodríguez-Pose A, Garcilazo E (2015) Quality of government and the returns of investment: examining the impact of cohesion expenditure in European regions. Reg Stud 49:1274–1290. https://doi.org/10.1080/00343404.2015.1007933

Rosenthal SS, Strange WC (2001) The determinants of agglomeration. J Urban Econ 50:197–229. https://doi.org/10.1006/juec.2001.2230

Rosenthal SS, Strange WC (2003) Geography, industrial organization, and agglomeration. Rev Econ Stat 85:377–393. https://doi.org/10.1162/003465303765299882

Rosenthal SS, Strange WC (2005) The geography of entrepreneurship in the New York metropolitan area. FRBNY Econ Policy Rev 11(2):29–53

Segarra A, Callejón M (2002) New firms' survival and market turbulence: new evidence from Spain. Rev Ind Organ 20(1):1–14. https://doi.org/10.1023/A:1013309928700

Spithoven A, Teirlinck P, Ysebaert W (2020) What determines the size of contract research from firms to universities? The role of geographical distance and regional co-location. Ind Corp Chang 29(6):1521–1538. https://doi.org/10.1093/icc/dtaa026

Spithoven A, Vlegels J, Ysebaert W (2021) Commercializing academic research: a social network approach exploring the role of regions and distance. J Technol Transf 46(4):1196–1231. https://doi.org/10.1007/s10961-019-09740-1

Strotmann H (2007) Entrepreneurial survival. Small Bus Econ 28(1):87–104. https://doi.org/10.1007/s11187-005-8859-z

Stuetzer M, Obschonka M, Davidsson P, Schmitt-Rodermund E (2013) Where do entrepreneurial skills come from? Appl Econ Lett 20(12):1183–1186. https://doi.org/10.1080/13504851.2013.797554

Uyarra E (2010) What is evolutionary about 'regional systems of innovation'? Implications for regional policy. J Evol Econ 20(1):115–137. https://doi.org/10.1007/s00191-009-0135-y

Wennberg K, Lindqvist G (2010) The effects of clusters of the survival and performance of new firms. Small Bus Econ 34(3):221–241. https://doi.org/10.1007/s11187-008-9123-0

Zucker LG, Darby MR, Brewer MB (1998a) Intellectual human capital and the birth of U.S. biotechnology enterprises. Am Econ Rev 88:290–306

Zucker LG, Darby MR, Armstrong J (1998b) Geographically localized knowledge: spillovers or markets? Econ Inq 36(1):65–86. https://doi.org/10.1111/j.1465-7295.1998.tb01696.x