Article

Urban Studies

Urban Studies
2020, Vol. 57(5) 996–1014

DOI: 10.1177/0042098018820241
journals.sagepub.com/home/usj

Knowledge proximity and firm innovation: A microgeographic analysis for Berlin

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Abstract
We analyse the geographic proximity of innovative firms to different types of knowledge sources in an urban environment on a microgeographic scale. Based on a comprehensive panel data set of manufacturing and service firms in the German capital city Berlin, we investigate the characteristics of firms' knowledge environment while differentiating by the type of innovation. Geocoded firm locations at the level of individual addresses allows us to describe the knowledge environment of firms on a very fine microgeographic scale. We find that innovative firms are located in places with higher numbers of same-sector firms, more start-ups and a higher inflow of other firms. They also locate in closer proximity to universities and research institutes. These differences decay rapidly within a few metres (50–250 m), indicating a truly microgeographic scope of knowledge sources in urban environments.

Keywords
agglomeration/urbanisation, economic processes, innovation, technology/smart cities

摘要
我们在微观地理尺度上分析创新企业与城市环境中不同类型知识来源的地理接近程度。基于德国首都柏林的制造和服务公司的综合面板数据集，我们在区分创新类型的基础上研究了企业知识环境的特征。单个地址层面的地理编码公司位置使我们能够以非常精细的微观地理尺度描述公司的知识环境。我们发现，创新型企业位于同行业公司数量较多、初创企业较多、其他企业流入较多的地方。它们也位于离大学和研究机构更近的地方。这些差异在数米（50-250米）内迅速衰减，表明了城市环境中知识来源地理辐射范围真实的微观特性。

关键词
集聚/城市化、经济过程、创新、技术/智慧城市

Received January 2018; accepted November 2018

Introduction

Knowledge spillovers are an important driver of innovation in firms. Using knowledge of others reduces the cost of innovation through input sharing and learning (Jaffe, 1986) and provides firms with ideas and technology they could not have developed based on their own capabilities. While knowledge spillovers may occur at any geographic scale, close proximity to external knowledge sources is likely to facilitate such spillovers (Audretsch and Feldman, 1996; Jaffe et al., 1993). Proximity eases exchange of workers among firms and hence the diffusion of knowledge embedded in people (Glaeser, 1999; Jovanovic and Nyarko, 1995; Jovanovic and Rob, 1989). Proximity also facilitates learning from observing, informal knowledge exchange through personal contacts of workers and managers, and knowledge exchange from joint business activities along the supply chain.

An urban environment provides an excellent ground for such knowledge flows (Audretsch, 1999; Feldman, 1999; Glaeser, 1999). Knowledge spillovers have hence been identified as one of the major sources for the emergence and growth of cities (Duranton and Puga, 2004; Marshall, 1890). There is strong empirical evidence that knowledge spillovers actually increase innovation performance in cities (Audretsch and Feldman, 2004; Feldman, 1999; Feldman and Audretsch, 1999; Henderson, 2007; Simmie, 2002). Less is known about the exact geographic scope of these spillovers, however. Many studies consider the entire stock of knowledge within a city as a source for spillovers (Audretsch and Feldman, 2004). When looking at proximity within a city, usually a rather large geographic scale is applied (Duranton and Overmans, 2005; Jang et al., 2017; Larsson, 2017; Murata et al., 2014; Rosenthal and Strange, 2008).

Recent research has paid more attention to the very local environment of a firm and how the configuration of a firm's direct neighbourhood and the local situation in which a firm operates affect knowledge exchange and innovation results (see Catalini, 2016; Kabo et al., 2014). These microgeographic studies, applying a very detailed scale of a few metres only, show that local environments provide special opportunities for meeting and contacting other innovative actors and can have a significant impact on innovation performance. Another recent strand of literature analysis the role of microgeographic configuration in a city (see Andersson et al., 2016, 2017). The concept of innovation districts within cities (Katz and Bradley, 2013; Katz and Wagner, 2014) is another recent approach that emphasises the role of microgeography for innovation in urban areas.

The present article links this microgeographic view with the literature on knowledge spillovers and innovation in an urban environment. By employing highly disaggregated geographic data on the location of knowledge sources and innovative firms in the German capital city Berlin, the article aims to contribute to the literature in two ways. First, we provide evidence on the role of microgeographic proximity within a city instead of treating a city as a single location. Second, we investigate how different knowledge sources (universities, research institutes, start-ups, other innovative firms) are geographically related to different types of innovation (product and process innovation, degree of novelty) which offers new insight into the role of knowledge diversity in a city for

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innovation. While this paper builds on the theoretical framework of knowledge spillovers, we do not empirically analyse knowledge spillovers as such.

Knowledge proximity and innovation in urban areas: A microgeographic perspective

A city is an ideal spot for accessing and exchanging knowledge that is critical to innovation. Innovative ideas of users, advanced technology from suppliers, new knowledge generated in science and research, innovations of other firms, or support from consultants and other service providers are often crucial inputs to innovation (Cassiman and Veugelers, 2006; Leiponen and Helfat, 2011; West and Bogers, 2013). In order to access this knowledge, firms do not only need absorptive capacities and adequate search strategies, they also need to interact with these external sources. Geographic proximity can certainly facilitate the exchange of knowledge (Figueiredo et al., 2015; Jaffe et al., 1993; Singh and Marx, 2013; Thompson, 2006). The more tacit knowledge is, the more important is face-to-face communication, mutual understanding, a common background and trust in order to learn from others (Audretsch and Feldman, 1996; Gertler, 2003; Howells, 2002). Combining specialised knowledge sources and diverse actors in a city helps to avoid lock-in that may emerge if close interaction among local actors restrict openness and searching beyond the local boundaries (Boschma, 2005).

Knowledge exchange can take place in different ways. One is when workers move between firms as much of the critical knowledge needed for innovation is embedded in workers (Combes and Duranton, 2006; Fosfuri and Rønde, 2004). Cities provide a particularly favourable environment for this type of knowledge exchange as workers can choose from many potential employers within a short commuting area from their home. Another way is to learn from observing and communicating with others (Duranton and Puga, 2004). Urban density clearly eases interaction, making urban areas a kind of school where entrepreneurs, managers and workers can continually add to their skills (Rosenthal and Strange, 2003). Urban density was also found to have a positive effect on wages, especially for university-educated workers, potentially capturing localised non-market interaction effects (Andersson et al., 2016). The concept of innovation districts introduced by Katz and Wagner (2014) also emphasises the role of local interaction between urban actors and infrastructures. They are becoming more important owing to the value of density and proximity in the evolution of a knowledge and technology driven economy and the emergence of open innovation approaches.

The link between local knowledge environments and innovation in firms is not a unidirectional one. Firms may not only seek for knowledge proximity, their innovation activities may also shape their local knowledge environment and affect innovation in other firms, owing to the public good property of innovation (Duranton and Puga, 2004). Close proximity between knowledge sources and innovative firms can hence form a local innovative milieu where actors mutually provide inputs for innovation (Gertler, 2003). The literature on innovative clusters has demonstrated how this process can form dynamic regional concentrations of innovative activities (see Audretsch, 2003; Feldman and Audretsch, 1999; Forman et al., 2016; Glaeser, 2000; Klepper, 2010; Porter, 1996; Saxenian, 1994).

A key but yet little-explored issue is the exact geographic scale at which the proximity to knowledge sources can stimulate innovation and knowledge spillovers. Personal interaction certainly facilitates this process

(Glaeser, 1999, 2000). The potential for personal interaction is assumed to decay rapidly with distance (Larsson, 2014). Close spatial proximity can also drive job-switching and associated knowledge flows (Larsson, 2017). Recent research has stressed the specific role of such microgeographic[1] configurations. Kabo et al. (2014) use path overlap within an academic research building as a measure of proximity and examine how physical space is shaping the formation and success of scientific collaborations. They find that when two researchers traverse paths with greater overlap, both their propensity to form new collaborations and to win grant funding for their joint work increase. Catalini (2016) shows that researchers' co-locations matter for the rate, quality and direction of scientific collaboration. Using data on research labs that were forced to move within a Paris university campus without being able to choose their new location, he found that collaboration between two labs increases significantly if the labs have moved to the same place, as long as the type of research done in both labs is sufficiently similar. Jang et al. (2017) demonstrate for the mobile gaming industry in Seoul that firms specialising in similar aspects of product innovation tend to locate in a single cluster within the city. Andersson et al. (2017) find that firms may benefit from both specialisation and diversification economies by locating in neighbourhood-level industry clusters within diversified cities.

While these microgeographic studies focus on collaboration and the performance of researchers and other individuals within the same organisation, there is little research on the role of the microgeographic configuration of the knowledge environment at the firm level. In this article, we analyse whether spatial proximity can play a decisive role for firms' innovation in urban areas. The direct neighbourhood to other firms and other knowledge providers may increase the chance of getting in contact with them and exchanging information, including coincidental contacts. Personal contacts can also facilitate the move of workers between firms. Direct neighbourhood may also increase the opportunity to observe activities of neighbours and stimulate learning.

We investigate the role of the local knowledge environment of innovative and non-innovative firms in urban areas, using Berlin as the place for our empirical analysis. Detailed firm address data allow for a microgeographic analysis at a scale of 50-m distances and below. At the same time, our data include information on innovation activities of a very large sample of firms in manufacturing and services in Berlin for a five-year period. This provides the opportunity to examine how innovation activities relate to changes in the innovation activities of surrounding firms, including relocations, start-ups and closures.

Our research is explorative in nature. The main aim is to describe the local knowledge environment of innovative and non-innovative firms and their spatial proximity to different knowledge sources on a microgeographic scale. We focus on three types of knowledge sources:

(1) The location of universities and research institutes as a major source of knowledge and talented people for innovative firms (Agrawal et al., 2014; Anselin et al., 1997; Feldman and Florida, 1994; Roper et al., 2017).
(2) Entrepreneurship clusters which provide both a source for innovation, and may challenge existing firms to respond to new market entries by increasing their own innovative efforts (Chatterji et al., 2014; Duvivier and Polèse, 2018; Glaeser et al., 2010).

(3) Micro-clusters of innovative firms that facilitate learning and specialisation in innovation (Boix et al., 2015; Jang et al., 2017).

Duranton and Puga (2001) stressed the importance to distinguish product and process innovation when analysing innovation in an urban environment. They showed that product innovation tends to be linked to diversified knowledge sources while cost-reducing process innovation are linked to more specialised places. We follow them and separate product from process innovation. In addition, we distinguish novel product innovations (new-to-the-market) from the imitation of innovative ideas and consider whether a firm conducts in-house R&D since different knowledge sources may be required for different degrees of novelty and types of innovative knowledge (Leiponen and Helfat, 2011; Rammer et al., 2009).

Methodology

When investigating the relation between a firm's local knowledge environment and its innovation activities, endogeneity problems emerge immediately. Since geography matters for innovation, firms will try to choose locations that fit best to their innovation activities and may locate in close proximity to other innovative firms and important knowledge sources (Leiponen and Helfat, 2011). This self-selection of innovative actors into certain urban neighbourhoods can be a main driver for the emergence of innovative districts within a city (Katz and Bradley, 2013; Katz and Wagner, 2014). Our data show that innovative firms indeed cluster in certain locations (see Figure 2) which suggests that a selection process may be at work. At the same time, locations may change their characteristics if they host innovative firms, e.g. if research institutes relocate towards existing innovative clusters.

We deal with this selection issue in two ways. For investigating differences in the local knowledge environment of innovative and non-innovative firms, it is important to consider firm characteristics which may affect both innovation decisions and the choice of location. We apply a matching approach (Heckman et al., 1998) to ensure that we compare innovative firms with non-innovative ones that share the same basic characteristics so that differences in the local knowledge environment cannot be attributed to these characteristics.

While matching is usually employed to identify treatment effects of policy intervention, the method is also useful for our purpose. We match each innovative firm i in our sample with a non-innovative firm j which shows the same basic characteristics. For this purpose, we estimate the propensity score for each innovative firm $P(x_i, \beta)$ and consider only innovative firms with common support, i.e. for which the probabilities do not exceed the maximum and do not fall below the minimum of the probabilities of non-innovative firms. x_i represents firm characteristics (size and age) and β is a parameter. In order to ensure that each pair of innovative and non-innovative firm comes from the same sector, we require exact matching for a firm's sector affiliation ($sec_i = sec_j$, sec being the 2-digit level of ISIC rev. 2). The difference δ between an innovative firm i and a non-innovative firm j (out of the entire group of non-innovative firms N^0) is given by:

$$\delta_{ij}^k = P^k\left(x_i', \hat{\beta}\right) - P^k\left(x_i', \hat{\beta}\right) \forall j = 1, \ldots, N^0 \tag{1}$$

Based on (1), we calculate the Malahanobis distance (MD)

$$MD_{ij} = \delta_{ij}{}^{k'} \Omega^{(-1)} \delta \forall j = 1, \ldots, N^0 for\, sec_i = sec_j \tag{2}$$

to find the nearest non-innovative firm j for each innovative firm i. Ω represents the covariance matrix based on non-innovative firms. Note that the matching is performed for each type k of innovation separately. Owing to the large data set we have at hand, the matching resulted in a high quality. The common support criteria was met for each innovative firm, and after matching size and age differences between innovative and non-innovative firms were completely insignificant. By ensuring that each innovative firm is matched with a non-innovative one from the same 2-digit sector, we take also into account the very different locational requirements of manufacturing and services firms.

The second approach to tackle endogeneity is to analyse whether changes in innovation activities of neighbouring firms in the past are correlated with a firm's current innovation activities in t. For this purpose, we consider five types of changes in innovation activities of firm j in period $t-1$ which is located in the neighbourhood n of firm i ($i \neq j$):

(1) transition of firm j from innovative to non-innovative between $t-2$ and $t-1$ (and vice versa) while firm j remains located in neighbourhood n in $t-2$, $t-1$ and t;
(2) moving in of an innovative or non-innovative firm j in $t-1$ into neighbourhood n (and staying in n in t);
(3) moving out of an innovative or non-innovative firm j in $t-1$ from neighbourhood n;
(4) foundation of a new firm j (innovative or non-innovative) in $t-1$ in neighbourhood n (which remains located in n in t);
(5) closure of a firm j (innovative or non-innovative) in $t-1$ in neighbourhood n.

We assume that past innovation dynamics in other firms are rather exogenous to a focus firm i's later innovation activities. At the same time, innovation dynamics in a firm i's local environment may alter the firm's opportunities for innovating. If neighbouring firms introduce innovations, innovative firms move into firm i's neighbourhood, or innovative start-ups open their business in firm i's neighbourhood, firm i may be stimulated by these activities and may learn for its own innovative efforts. Similarly, the loss of an innovative environment because of closures or moving out of innovative firms or stopping of innovative activities in neighbouring firms might discourage innovation in firm i. In order to test the relation between past innovation dynamics in the local environment on current innovation IN in firm i, we run the following regression model:

$$IN^k_{i,t} = \alpha + \sum_m \beta^k_m ID^k_{mj,t-1} + \sum_l \gamma_l CT_{li,t} + \varepsilon_{i,t} \; i \neq j; n_i = n_j \tag{3}$$

ID represents the different types m of innovation dynamics variables (transition of status, moving in and out, start-up and closure of firms) based on the number of firms reporting a respective dynamic in firm i's neighbourhood n. CT represents control variables l that may affect firm i's innovation decision in t, such as size, age and sector. α is a constant, β and γ are parameters to be estimated, and ε is the error term.

In both the matching and the regression model approach, we consider five types k of innovative firms:

(1) innovator (product and/or process)
(2) product innovator (goods and/or services)
(3) new-to-market innovator (i.e. novel product innovation)
(4) process innovator

(5) firms with continuous in-house R&D activity

Note that firms can have different types of innovations in the same period. All indicators refer to well-established definition and measures proposed in the Oslo Manual (OECD and Eurostat, 2005) and applied in the Community Innovation Surveys (CIS) of the European Commission and are measured in a binary (yes/no) way. Such indicators are well suited for measuring innovation in small firms since small firms usually only have one or few innovations within a certain period of time. The chosen indicators are also well suited for capturing innovation both in manufacturing and services. Using quantitative indicators such as R&D expenditure or sales with new products is often less useful as they can be subject to extreme values in small firms and may overrate differences in innovation performance (see Rammer et al., 2009). As about 80% of the firms in our empirical study are small firms with fewer than 50 employees, and about 70% are from service sectors, we believe that the choice of binary indicators is adequate for our study.

Data

The empirical analysis is based on a unique panel data set on innovation activities of Berlin-based firms, the 'Berlin Innovation Panel'. This panel survey has been initiated in 2012 by the Technical University of Berlin and has received funding since 2013 from the *Technologiestiftung* Berlin. The survey covers all legally independent enterprises with five or more employees in manufacturing and knowledge-intensive services[2] that are headquartered in Berlin. The survey is conducted as part of the German Innovation Survey,[3] which is the German contribution to the CIS. It shares all methodological features with the CIS, including questionnaire design, quality control and data processing routines (see Peters and Rammer, 2013, for more details). The Berlin Innovation Panel as well as the German Innovation Survey are conducted by the Centre for European Economic Research (ZEW) as a voluntary mail survey (including an online response option) on an annual base. This paper uses the first five waves of the Berlin Innovation Panel conducted in the years 2012 to 2016 which cover the reference years 2011 to 2015.

The gross sample of the survey includes basically all firms of the target population of the survey and has been refreshed in 2013 and 2015 to compensate for firm closures and firms moving out of Berlin. Panel mortality is substantially high in the Berlin panel, reflecting high dynamics in the urban firm sector. The response rate of the survey is around 20%, which is somewhat lower than the response rate in the German Innovation Survey (25–30%), reflecting a lower propensity of survey participation among smaller firms. Following the German Innovation Survey, the Berlin Innovation Panel includes a comprehensive non-response survey which collects information on the presence of product and process innovation as well as in-house R&D activities, applying the same definitions as the paper/online questionnaire. The non-response survey is based on a stratified sample of non-responding firms and is conducted by telephone. The number of firms covered by the non-response survey exceeds the number of responding firms, leading to a high share of firms from the gross sample for which innovation-related information has been collected (between 42% and 47%). Table 1 provides details on the sample size of the Berlin Innovation Panel.

The high dynamics in the Berlin firm sector reduces the panel nature of the data. In the first five survey years, a total of 7936

Table 1. Sample size of the Berlin Innovation Panel.

Survey year	Gross sample (#)	Not utili-sable[a] (#)	Responses (#)	Non-response (NR) survey (#)	Response rate (%)[b]	Response rate incl. NR (%)[b]
2012	4927	908	770	909	19.2	41.8
2013	5275	914	806	1101	18.5	43.7
2014	4886	782	752	997	18.3	42.6
2015	4810	918	791	1048	20.3	47.3
2016	4002	554	707	901	20.5	46.6

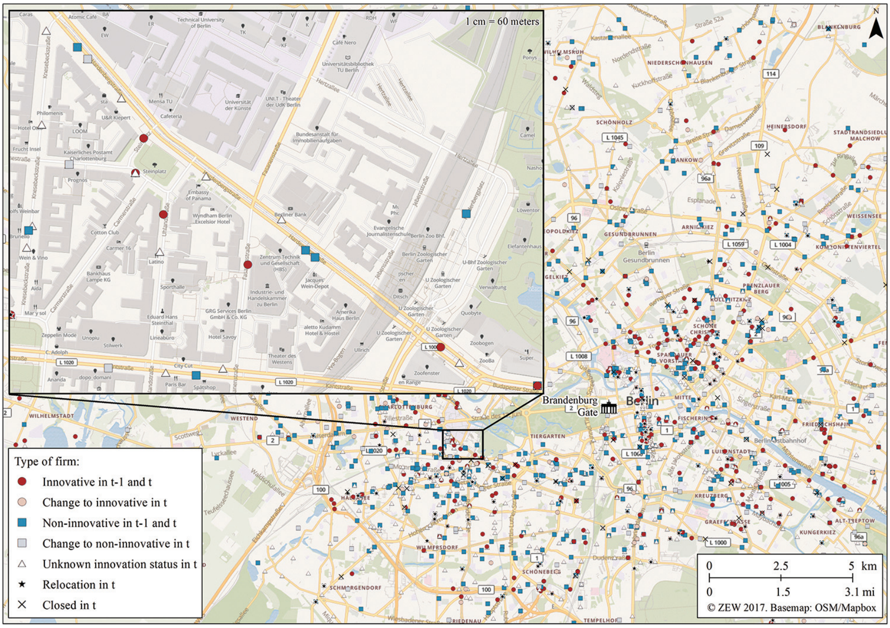
Notes: [a]Firm closure, moving out of Berlin, wrong address because of relocation, etc.
[b]As a percentage of gross sample net of not utilisable addresses.

different firms have been surveyed, but only 2092 firms were surveyed in all five years. As the unbalanced nature of the survey limits our analysis with respect to measuring innovation activities that take place in a firm's neighbourhood, we extended the data set towards a more balanced panel by interpolating and extrapolating observations. For this purpose, we exploit additional data from the Mannheim Enterprise Panel (MEP), which is the sampling pool for the survey,[4] on firm foundation and closure. Annual address, employment and sector data from the MEP are used to fill in geographic, employment and sector information. For innovation indicators, inter- and extrapolation is facilitated by the fact that each indicator refers to a three-year reference period, following the common practice of the CIS and the recommendations of the Oslo Manual (OECD and Eurostat, 2018). Details on the procedure are provided in the Supplementary Material (available online). In that way, we extended the total number of year-firm observations to 13,405.[5] The more balanced panel contains 3723 different firms. The average number of observations per firm is 3.6.

Address information for each firm in each year allows us to exactly geolocate firms and to calculate distances to other knowledge sources at a scale of 50 m and below. Details about geocoding of the address data are provided in the Supplementary Material (available online). Figure 1 illustrates the geographic detail of our firm-level innovation status data for the central area of Berlin.

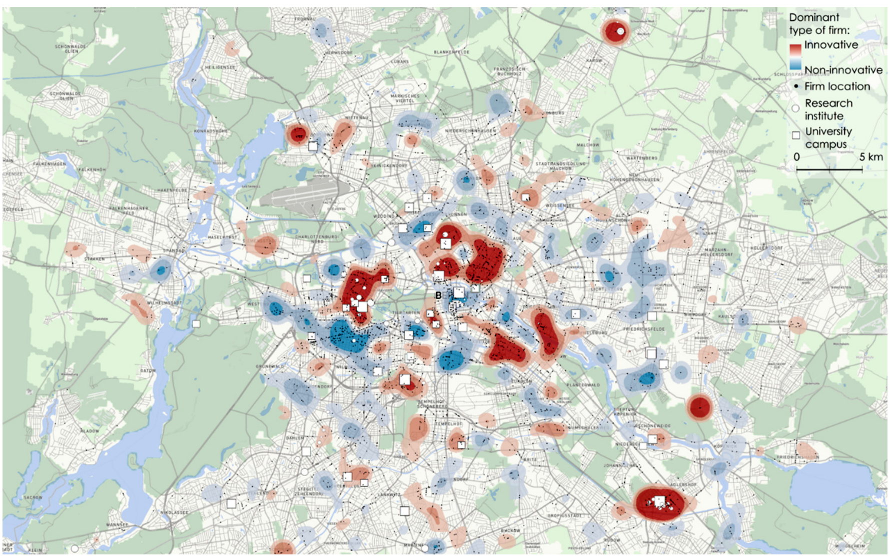
Data on the five innovation indicators and on firm-level control variables are taken directly from the survey. While innovation is self-reported by firms, there are no incentives for firms to over- or under-report innovation. To clarify the concept of innovation, the survey includes examples for different types of innovations for the sector of the firm. 39.0% of the firms in our sample have introduced an innovation. 31.2% are classified as product innovators, 5.4% have introduced a market novelty, 24.4% are process innovators and 21.2% conduct in-house R&D continuously. The average size of firms is 86 employees (at full-time equivalents) and the average age of the firms is 21 years. 34.4% of the firms are from manufacturing sectors (including construction, energy and water supply, and waste treatment) and 65.6% from service sectors.

The geographic distribution of innovative and non-innovative firms is highly uneven. Figure 2 shows for product/process innovators a number of clusters with a high share of innovative firms as well as areas with predominantly non-innovative firms. Some



Basemap: MapBox/OSM

Figure 1. Example for the geographic distribution of firms in Berlin by innovation status.



Basemap: MapBox/OSM

Figure 2. Clusters of innovative and non-innovative firms (product or process innovators) in Berlin.

Table 2. Location indicators.

Group	Indicator	Short name	Unit
Universities,	Universities	uni_[d]	No. of students
research institutes	Research institutes	ins_[d]	No. of researchers
Entrepreneurship	Firms moving in	fin_[d]	No. of firms
	Start-up activity	st_[d]	No. of firms
Micro-clusters	Stock of firms in same sector	fst_[d]	No. of firms
Innovation dynamics	Incoming innovators/non-innovators	in[k]1_[d]/in[k]0_[d]	No. of firms
	Outgoing innovators/non-innovators	ot[k]1_[d]/ot[k]0_[d]	No. of firms
	Transition into/out of innovator	ch[k]1_[d]/ch[k]0_[d]	No. of firms
	Innovative/non-innovative start-ups	nf[k]1_[d]/nf[k]0_[d]	No. of firms
	Closing innovators/non-innovators	cl[k]1_[d]/cl[k]0_[d]	No. of firms

Notes: [d]: alternative distance thresholds: 50 m, 100 m, 250 m 500 m, 1000 m, 2500 m; [k]: type *k* of innovation activity.

clusters relate to Katz and Wagner's (2014) 'anchor plus' model which describes innovation districts with a rich base of related firms, entrepreneurs and spin-off companies in downtown and mid-town areas of central cities centred around a major anchor institution (e.g. the Charlottenburg district around the Technical University) while others represent 're-imagined urban areas' (industrial or warehouse districts that underwent transformation, e.g. Friedrichshain). The Adlershof and Buch clusters in the southeast and the northeast correspond to Katz and Wagner's 'urbanised science park' type. More details on these clusters and their sector composition is provided in the Supplementary Material (available online).

The maps shows the difference in local firm densities between innovative and non-innovative firms The densities are based on kernel density estimation using triweight kernels with radius 1.5 km and identical weights (1.0) for all firms. In order to facilitate the visual presentation, the kernel density raster of innovative firms was multiplied by the relation of non-innovative to innovative firms.

Four groups of indicators describe the local knowledge environment of a firm (see Table 2).

(1) Universities and research institutes: number of students in universities and number of researchers in research institutes in firm *i*'s neighbourhood *n* in year *t*. The data have been collected based on our own inquiry and include 63 locations of universities and 83 locations of research institutes (see Figure 2).
(2) Entrepreneurship: number of firms newly started in firm *i*'s neighbourhood *n* in $t-1$, number of firms that moved into firm *i*'s neighbourhood in $t-1$ (either from Berlin or from elsewhere), considering only the sectors that are covered by the Berlin Innovation Panel. Data are taken from the MEP.
(3) Micro-clusters: number of firms active in the same 2-digit sector as firm *i* in firm *i*'s neighbourhood *n* in year *t*. Data are taken from the MEP.
(4) Innovation dynamics: number of firms in firm *i*'s neighbourhood *n* that changed their innovation status between years $t-1$ and *t*, including firms that have changed their innovation status, firms that moved in or out of the neighbourhood, and firms newly founded or closed. Data are taken from the Berlin Innovation Panel.

For defining a firm *i*'s neighbourhood *n*, we use six different distance thresholds: 50, 100, 250, 500, 1000 and 2500 m, measured as direct distance from the building in which a firm is located to the location of other firms, universities and research institutes. Descriptive statistics for all model variables, including data on innovation dynamics of firms by type of innovation, can be found in the Supplementary Material (available online).

Empirical results

Local knowledge environment of innovative firms

The result of the matching analysis reveals significant differences in the local knowledge environment of innovative and non-innovative firms in Berlin (see Table 3). For both product and process innovators we find statistically significant positive differences to non-innovators for the proximity to research institutes (*in_[d]*). An innovator on average has three researchers from public research institutes located within a 50 m radius, which is 79% more than for non-innovators. The difference is monotonously declining with increasing distance. The proximity to research institutes is significant up to a distance of about 1 km (except process innovators: 0.5 km).

For universities (*uni_[d]*), we find that within a distance of 0.5 to 1 km, the number of university students in a firm's neighbourhood is significantly higher for all product innovators and market novelty innovators while we do not find significant differences for smaller distances. This result may reflect the fact that most university buildings are rather huge and often located next to each-other on a campus, leaving little space for other firms to locate nearby, except for firms that provide direct services to the university or to students (e.g. printing shops, facility management). Consequently, other firms will have to choose locations that are rather distant from the university buildings.

Another significant difference relates to the proximity to other firms that recently have moved into a firm's neighbourhood (*fin_[d]*). A product innovator has on average 2.8 new neighbours in a 50 m radius, and 4.8 in a 100 m radius. This is 19% and 15% more than for firms without product innovation. Product innovators also show a larger number of recent start-ups (*st_[d]*) in their neighbourhood, exceeding the number of start-ups of firms without product innovation by 14% in a 100 m radius. We do not find higher local firm dynamics for process innovators. In addition, we find some indication of localisation economies for product innovators as the number of firms from the innovating firm's sector (*fst_[d]*) within a 250 m radius is significantly higher.

For market novelty innovators, the results largely correspond to those for product innovators. A main difference relates to localisation economies. Firms with market novelties are located in much closer proximity to other firms from their sector as compared with similar firms without market novelties. The number of same-sector firms (*fst_[d]*) located within a 50 m radius is 39% higher. The number of firms that have moved into the direct neighbourhood (*fin_[d]*) is 49% higher for a 50 m radius and 36% higher for a 100 m radius. The same holds for the number of start-ups (*st_[d]*). Significant positive differences can be observed up to 250 m for firms moving in (*fin_[d]*) and for start-ups (*st_[d]*), and up to 1 km for firms in the same sector (*fst_[d]*). For the proximity to research institutes and universities the results are similar to those for all product innovators.

For firms conducting in-house R&D on a continuous basis we find similar location patterns as for firms with market novelties. They show a higher number of firms in the same sector (*fst_[d]*) up to a 500 m radius. For the

Table 3. Differences in the proximity to knowledge sources by type of innovation: Results of matching analyses.

Variable	Innovator			Product innovator			Market novelty			Process innovator			Continuous R&D		
	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value
uni_50	11	−21	−0.28	11	22	0.38	6	0	0.00	17	52	1.09	11	41	0.61
uni_100	21	−1	−0.01	22	24	0.56	7	−9	−0.07	21	4	0.07	26	69	1.77
uni_250	147	16	0.75	164	19	0.93	157	32	0.69	159	16	0.70	188	56	2.73*
uni_500	982	25	2.99*	1068	27	3.22*	1517	48	3.28*	897	8	0.74	1356	52	6.85*
uni_1000	2760	14	2.51*	2928	17	3.03*	3657	43	4.47*	2622	4	0.55	3249	35	6.03*
uni_2500	12188	−2	−0.53	12437	2	0.48	12875	11	1.54	12086	−3	−0.66	12949	11	2.70*
ins_50	3.3	79	4.86*	3.7	76	4.36*	6.9	66	2.24*	3.1	70	3.65*	5	69	3.82*
ins_100	8.8	55	4.49*	9.3	52	3.76*	13	51	2.15*	7.8	30	1.78	12	51	3.81*
ins_250	48	40	4.35*	53	46	5.00*	76	51	2.85*	47	28	2.68*	76	63	7.58*
ins_500	117	31	4.73*	128	38	5.76*	194	51	4.21*	114	18	2.35*	161	56	9.10*
ins_1000	286	17	3.06*	305	22	4.00*	398	36	3.52*	280	8	1.22	342	34	6.18*
ins_2500	1192	0	0.10	1219	5	1.45	1275	9	1.16	1158	−7	−1.72	1244	7	1.62
fst_50	0.5	−1	−0.16	0.5	11	1.39	0.8	39	2.92*	0.4	−17	−1.71	1	26	3.14*
fst_100	0.7	1	0.12	0.7	12	1.77	0.9	30	2.40*	0.6	−11	−1.30	1	26	3.68*
fst_250	1.7	7	1.51	1.8	14	2.94*	2.5	34	3.71*	1.7	4	0.67	2	23	4.34*
fst_500	4.0	3	0.63	4.2	6	1.42	5.2	26	3.07*	3.9	3	0.50	5	13	2.71*
fst_1000	11	0	−0.07	11	3	0.64	13	19	2.19*	11	−2	−0.44	12	7	1.44
fst_2500	43	−8	−2.10*	44	−9	−2.08*	43	−2	−0.24	42	−8	−1.89	44	−7	−1.43
fin_50	2.6	17	1.81	2.8	19	2.00*	4	49	2.69*	2.5	−9	−0.77	3	25	2.75*
fin_100	4.6	13	1.96*	4.8	15	2.25*	6	36	2.51*	4.4	−5	−0.67	5	18	2.41*
fin_250	15	4	0.74	16	9	1.67	18	29	2.84*	15	0	0.02	16	6	1.01
fin_500	44	−7	−1.34	45	1	0.15	47	14	1.36	44	−6	−1.16	46	0	0.05
fin_1000	140	−8	−1.98*	144	0	−0.02	142	6	0.60	139	−9	−2.03*	146	1	0.16
fin_2500	646	−5	−1.56	657	−1	−0.19	650	5	0.71	644	−6	−1.89	674	2	0.58
st_50	0.2	12	1.28	0.2	13	1.35	0.3	51	3.14*	0.2	1	0.05	0	14	1.24
st_100	0.4	14	2.12*	0.5	14	1.98*	0.5	34	2.34*	0.4	4	0.53	0	11	1.26
st_250	1.7	5	0.89	1.7	9	1.62	1.9	24	2.02*	1.7	5	0.83	2	4	0.59
st_500	5.2	−1	−0.11	5.3	1	0.28	5.5	13	1.20	5.3	3	0.51	5	2	0.38

(continued)

Table 3. Continued

Variable	Innovator			Product innovator			Market novelty			Process innovator			Continuous R&D		
	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value	mean	diff	*t* value
st_1000	17	0	−0.06	18	1	0.18	17	10	1.05	18	0	−0.09	18	4	0.72
st_2500	80	−2	−0.52	80	−1	−0.25	79	8	1.02	80	−1	−0.19	80	2	0.57
# obs.[a]	4119 / 5924			3305 / 6778			2558 / 7584			592 / 7158			318 / 7510		

Notes: $^*p < 0.05$. diff: difference to control group in %. [a]Number of innovative/non-innovative firms.

number of ingoing firms (*fin_[d]*), significant effects are confined up to a 100 m radius. In addition, proximity to research institutes (*ins_[d]*) is much higher for continuously R&D performing firms. They also tend to be located closer to university campuses (*uni_[d]*) than any other type of innovation active firms. Proximity to start-ups (*st_[d]*) is not higher for firms with continuous R&D.

The results presented above refer to firms across all sectors. While the matching approach controls for firm sector affiliation, there might be a systematic difference between manufacturing and services owing to the different role of external knowledge sources in their innovation process. When matching separately for manufacturing and service firms (for results see the Supplementary Material, available online), we find that the results hold for manufacturing but not for services, except for continuous R&D where we also see that service firms with continuous R&D are located in closer proximity to universities and research institutes, and they have a larger number of other firms nearby.

Innovation dynamics in a firm's neighbourhood

The second part of our empirical analyses investigates the role of prior changes in other firms' innovation activity in the neighbourhood of a focal firm. These changes refer to firms already located in the area which start or stop to innovate (including closures) or move in or out (including start-ups). We assume that a firm's innovation of type k is particularly affected if changes in the same type of innovation occur nearby. In order to limit the variety of results, we define a firm's neighbourhood by a 250 m radius only since the analysis in the previous section has shown that the 250 m distance threshold is often a demarcation between significant and insignificant differences in location patterns. We use regression models to analyse the link between a firm's innovation activities ('dependent variable') and innovation dynamics in its neighbourhood ('independent variable') while controlling for size, age and sector. Our results should be interpreted as correlations and not causal effects, as we cannot rule out that past innovation dynamics in a firm's local environment were influenced by the firm's current innovation activities, considering the steady-state nature of innovation.

We use three different dependent variables: (a) the probability of a firm i to report innovation of type k in year t (irrespective whether firm i has reported the same type of innovation in $t-1$), (b) the probability of a firm i to enter into innovation k in t (i.e. firm i hat no innovation of this type in $t-1$), and (c) the probability of a firm i to stop innovation k in t (while having reported this type in $t-1$). All independent variables are measured as change in the innovation status of neighbouring firms between $t-2$ and $t-1$. The estimation results are shown in Table 4.

We find that firms have a higher propensity to introduce a product innovation if other firms in their neighbourhood started or stopped product innovation activity in the year before. The estimated marginal effect is rather low: 1.2 percentage points for 'positive' innovation dynamics and 2.1 percentage points for 'negative' dynamics, compared to an average share of product innovators in the sample of 31.6%.

If other firms in the neighbourhood introduced a market novelty in the previous year, or if firms with market novelties moved away or ceased business, the probability to introduce a new-to-the-market innovation increases significantly. The estimated marginal effects are quite large: 3.8 percentage points if firms with a market novelty moved out and 6.6 percentage points if firms with market novelties closed. In case neighbouring firms have introduced such innovations in the previous period we find a much smaller value (0.9 percentage points, the average share of firms with market novelties is 5.9% in our sample).

The probability to introduce a process innovation increases if neighbouring firms have introduced process innovations in the previous year. The estimated marginal effect is 1.4 percentage points, while the average share of process innovators in the sample is 24.6%. This finding indicates a kind of local learning effect if firms can observe process innovation activities of their neighbours. For continuous R&D, we find similar results as for product innovation. If neighbouring firms started or stopped continuous R&D activities in the previous year, the probability to conduct continuous R&D increases. A high turbulence in local R&D activities seems to stimulate a firm's own R&D. In addition, the probability decreases if firms without continuous R&D moved into the neighbourhood.

We also run the regression analysis separately for manufacturing and service firms. Again, most of the above findings are confirmed for manufacturing firms but fewer for services, except for the findings on process innovation and continuous R&D which mainly apply to services. Owing to the lower number of observations in the split models, fewer statistically significant results are found.

Discussion and conclusion

This article made an attempt to explore the role of proximity to knowledge sources for innovation in firms in an urban environment. Using panel data on Berlin-based firms and exact address data, we investigated the firms' knowledge environments at a microgeographic scale, zooming into a firm's neighbourhood at the level of individual buildings.

When controlling for size, age and sector, we find that innovative firms, opposite to non-innovative firms, are located in places with a much higher number of other firms

Table 4. Estimation results of probit models on past innovation dynamics in a firm's neighbourhood and the firm's current innovation activities.

	Innovation		Product innovation		Market novelty		Process innovation		Continuous R&D	
	m.E.	std.err.	m.E.	std.err.	m.E.	std.err.	m.E.	std.err.	m.E.	std.err.
in1	−0.014	0.020	−0.021	0.022	0.013	0.026	0.008	0.022	−0.006	0.019
in0	0.025	0.020	0.008	0.017	−0.003	0.006	0.012	0.013	−0.027	0.013*
ot1	0.013	0.019	0.001	0.020	0.038	0.016*	−0.017	0.022	0.014	0.016
ot0	0.032	0.021	0.025	0.017	0.007	0.005	0.019	0.013	0.019	0.013
ch1	0.010	0.005	0.012	0.005*	0.009	0.005*	0.014	0.005*	0.023	0.011*
ch0	0.012	0.008	0.021	0.008*	−0.001	0.005	0.007	0.006	0.021	0.008*
cl1	−0.028	0.034	0.013	0.035	0.066	0.025*	−0.027	0.037	0.028	0.052
cl0	−0.024	0.035	−0.004	0.029	0.015	0.011	−0.019	0.025	0.000	0.022
nf1	0.133	0.143	−0.036	0.154	[a]		0.321	0.216	0.053	0.054
nf0	−0.032	0.040	0.014	0.034	0.004	0.013	−0.022	0.029	0.022	0.026
lna	−0.024	0.008*	−0.023	0.008*	0.009	0.002*	−0.016	0.007*	−0.024	0.007*
lnb	0.067	0.005*	0.053	0.004*	0.148	0.082*	0.059	0.004*	0.044	0.004*
LR Chi^2	1015.5		1103.5		372.9		467.5		1,209.8	
Pseudo R^2	0.112		0.131		0.168		0.062		0.179	
# observations	6736		6742		4915		6754		6311	

Notes: All models include sector dummies. [a]Variable omitted because of perfect correlation with dependent variable. *$p < 0.05$.

and start-ups in close vicinity (less than 250 m) and with a higher inflow of other firms. Close proximity to research institutes and universities is another distinctive feature of innovative firms. This finding is in line with a large number of studies that emphasise the role of local knowledge exchange between science and industry as a key factor of innovation (Anselin et al., 1997; Jaffe et al., 1993). What our study shows is that the geographic scope of this exchange seems to be very confined, at least in the context of urban spaces. Concerning the proximity to research institutes, the concentration of innovative firms already decreases beyond a 50 m radius. Beyond a distance of 1 km, we do not find a significant relation anymore. Product innovators and firms with continuous R&D in particular are very closely located to science and education institutions. These results point to the importance of opportunities for meeting each other in micro-spaces (Catalini, 2016; Kabo et al., 2014). The role of researcher mobility between universities, research institutes and firms in the innovation process may also enhance close proximity between them (Kaiser et al., 2015). In addition, some innovative firms may be spin-offs from research facilities or firms that choose a science park location in order to establish or ease interactions with science (see Löfsten and Lindelöf, 2002; Phan et al., 2005). However, the share of innovative firms located in science parks in all innovative firms in Berlin is at about 7%, implying that the overall results cannot be determined by this small group.

Another important finding of our analysis relates to the role of microgeographic industrial clusters. For firms with market novelties or continuous in-house R&D, close proximity (up to 250 m) to other firms from the same sector is a distinctive feature. In addition, a firm's probability to introduce a new-to-market innovation increases significantly if neighbouring firms have introduced such innovations in the previous period. These results hold across all industries, pointing to a general micro-scale localisation advantage in urban areas that can be related to learning from observing nearby competitors. Again, our contribution to the literature is that localisation economies in urban areas seem to operate on a very small geographic scale, which is in line with some sector-specific studies (see Arzaghi and Henderson, 2008; Jang et al., 2017).

The innovation dynamics in a firm's neighbourhood in the recent past (defined as changes in innovation activities in other firms located within a 250 m radius) do show some relation to current innovation in firms. As both 'positive' and 'negative' changes do play a role, it seems that local turbulence in innovation can motivate firms to consider innovation for themselves.

This research is a first attempt to zoom into the role of knowledge proximity for innovation in the city at a microgeographic level. While we believe that some of our results widen our understanding of the relation between localised knowledge and firm innovation, many important research questions remain open. First, we refrained from examining the exact urban environment in which a firm operates, e.g. urban infrastructure, density or amenities. In that way, our study is somewhat blind to the urban context that shapes innovation districts in cities (Katz and Bradley, 2013; Katz and Wagner, 2014). In future studies, one should compare the role of knowledge proximity for different innovation districts within a city.

Second, we can only observe correlations between innovation and local knowledge sources. We do not know to what extent firms actually interact with these knowledge sources and how knowledge is exchanged. Third, though we do have panel data, the limited length of our time series (5 years) prevents a more in-depth analysis of how changes in the local knowledge environment are associated with changes in innovation.

Finally, our results are based on an analysis across a large number of sectors of the urban economy. Analysis for a specific sector may add further insight as sectors may use different knowledge sources.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Notes

1. 'Microgeographic' refers to a micro-scale of spatial analysis that allows differentiation at a distance level of a few metres.
2. NACE rev. 2 divisions 10 to 39 (manufacturing) and 58 to 66, 70 to 74 (knowledge-intensive services).
3. Berlin-based firms surveyed in the German Innovation Survey are also part of the data set of the Berlin Innovation Panel.
4. The MEP (see Bersch et al., 2014, for details) is a kind of business register based on information collected by Germany's largest credit rating agency, *Creditreform*, and is maintained by ZEW. These data also serve as the base for the German firm data in the Bureau-van-Dijk company databases Amadeus and Orbis.
5. We also run the analyses based on the original data before inter- and extrapolation and found the same results, often at a higher level of statistical significance (see the Supplementary Material, available online).

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