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Local knowledge spillovers and innovation persistence of firms

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ABSTRACT

Innovation activities of firms tend to be highly persistent. Yet, little is still known about potential spatial contingencies affecting the degree of persistence. This paper analyses the influence of local knowledge spillovers on firms' persistence in innovation activities. Using a representative panel data set of firms in Germany from 2002 to 2016, complemented by detailed geographic information of patent activity over discrete distances to proxy local knowledge spillovers, we find that the local patenting activity positively moderates persistency in innovation activities. Estimations with different distance bands show that the strength of knowledge spillovers that contribute to innovation persistence attenuates with increasing distance and vanishes beyond 30 kilometres in manufacturing and beyond 20 kilometres in services.

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1. Introduction

Innovation is one of the main sources of economic growth. As successful innovation – the introduction of new products or processes that outperform existing products and processes – requires continuous commitment, the persistency of firms' innovation activities has attracted increasing attention of policy makers and researchers. Over the past two decades, a large body of literature has analysed innovation persistence at the micro level both empirically as well as from a theoretical perspective (see, for example, Cefis and Orsenigo 2001; Peters 2009; Raymond et al. 2010, amongst others). This literature demonstrates that firms exhibit strong persistency in their innovation behaviour.

Innovation persistence describes the situation that a firm conducts innovation activities, or introduces innovations, in consecutive periods of time. It can result from true state dependence (Heckman 1981) when there is a causal relationship between the decision to engage in innovation activity in one period and the propensity to conduct innovation activities in the following period. From a theoretical perspective, true state dependence can be linked to (1) fixed costs (as entry barrier) and sunk costs (as exit barrier) (Sutton 1991), (2) 'success breeds success' (Flaig and Stadler 1994), (3) accumulation of knowledge and learning effects (Geroski, van Reenen, and Walters 1997), and (4) market structures that either stimulate or discourage innovation (Woerter 2014). Persistence in innovation may also result from certain firm-specific characteristics such as firm size or managerial skills and attitudes that are positively associated with a higher or lower probability of innovating. As these characteristics are usually highly persistent over time, this also leads to observed persistence in innovation behaviour, and thus spurious state dependence may be

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identified (Peters 2009) if such observable and unobservable firm characteristics are not controlled for. The literature has found compelling evidence for true state dependence and has also analysed several firm internal drivers of persistence (see Le Bas and Scellato 2014; Crespi and Scellato 2015; Tavassoli and Karlsson 2015; Antonelli, Crespi, and Scellato 2013; Clausen et al. 2012; Raymond et al. 2010; Ganter and Hecker 2013; Cefis and Orsenigo 2001).

Little attention has been paid, however, to the role of locational factors, and local knowledge spillovers in particular, for innovation persistence. This is somewhat surprising as the literature on regional innovation stresses the importance of local knowledge spillovers for the regional concentration of innovative firms (Audretsch 2003; Audretsch and Feldman 1996a; Feldman and Florida 1994; Moreno, Paci, and Usai 2005a, 2005b). An extensive strand of literature has carved out the critical role of regional knowledge spillovers for the propensity to innovate, the spatial concentration of innovation activities, and the emergence of regional innovation systems (see, for example, Audretsch and Feldman 2004; Breschi and Lissoni 2001; Fritsch and Franke 2004; Carlino and Kerr 2015; Rodríguez-Pose and Crescenzi 2008). Analysing the contribution of local knowledge spillovers to the persistence of innovation can provide an important micro-foundation for better understanding the emergence of innovative regional clusters. In fact, the local knowledge environment of a firm can provide incentives to take-up, continue, or discontinue innovation activities. For example, locally available knowledge can reduce entry costs and sunk costs of innovation activities, which could result in higher entry and exit, greater fluctuations, and thus lower persistence. But locally available knowledge can also facilitate learning effects by providing easy and cheap access to complementary resources required for a firm's innovation activity. All this could increase innovation persistence.

Only few studies have yet looked at the role of regional knowledge spillovers for the persistence of innovation activities in firms. Among those few, Tavassoli and Karlsson (2018) look at the role of different regional settings on innovation persistence for firms in Sweden. They find that firms in regions with a greater number of innovative firms are more persistent innovators. In contrast, a recent study by Nam and Bao Tram (2021) compares the innovation and export persistence of Vietnamese SMEs in provinces with high and low regional competitiveness, respectively, and claims that persistence is higher in weaker business environments. Hence, this scarce existing empirical evidence on the role of the local knowledge environment for innovation persistence is not yet conclusive.

The aim of this paper is to provide additional and more robust empirical evidence on the role of a firm's local knowledge environment on the persistence of the firm's innovation activities. We use a representative, comprehensive panel data of firms in Germany that covers a 15-year period and define persistence of innovation as a situation in which a firm has spent financially on activities to develop and implement new products and processes in two consecutive years. The paper advances the literature in two important aspects. First, instead of using a general measure to proxy knowledge spillovers, such as the number of innovative firms (as used by Tavassoli and Karlsson 2018) or a regional innovativeness index (employed by Nam and Bao Tram 2021), we measure the local knowledge environment by the number of patents filed by other firms in the vicinity of the focal firm and in technology fields that are relevant to the focal firm's innovation activities. Secondly, we go beyond pre-defined regions as geographical units of analysis and employ a spatially highly detailed distance-based approach. Using geographic information systems (GIS), we calculate technology relevant patent counts over discrete distances based on ZIP codes, which represent very small geographic areas with a radius of 2 kilometres on average.

We study two potential effects of local knowledge spillovers on innovation persistence. The *direct effect* measures the contribution of localised knowledge to the firms' decision to engage in innovation activities. As the local knowledge pool itself is rather persistent, a positive direct effect in every period will contribute to a persistent innovation pattern. The *moderating effect*, which represents the interaction of a firm's local knowledge environment with the firm's lagged innovation status, measures the extent to which localised knowledge influences the effect of past on future innovation activities and thus contributes to innovation persistence by affecting true state dependence.

We find evidence for both effects. First, a greater pool of relevant technological knowledge around a firm significantly increases the probability of conducting innovation activities. The direct effect is limited to the service sector, however. We do not find such a knowledge pool effect for manufacturing firms. Secondly, the local patenting activity positively moderates persistency in innovation activities in both manufacturing and services. This double-effect of local knowledge spillovers can explain the growing concentration of innovation and the widening of spatial disparities in innovation performance that has in fact recently be observed (Castellani 2017; Rammer and Schubert 2018; Kerr and Robert-Nicoud 2020). Estimations with different distance bands between the firm's location and the surrounding patents show that the role of knowledge spillovers for innovation persistence fades with increasing distance. It becomes weaker beyond a 10 kilometres radius and vanishes beyond 30 kilometres. Again we find differences between manufacturing and services. As the knowledge used for innovation in services may be more intangible, tacit and tied to individuals than in manufacturing, effects of localised knowledge on innovation persistence may be spatially more constrained in services. Our results confirm this view.

The remainder of this paper is organised as follows. Section 2 discusses the role of local knowledge spillovers for innovation persistence of firms. Section 3 describes the data and presents some descriptive results. Section 4 presents our estimation approach. The results are presented in Section 5. Section 6 offers conclusions.

2. Theory: local knowledge spillovers and innovation persistence

For analysing the moderating role of local knowledge spillovers for innovation persistence, we link two strands of literature that have largely developed separately. On the one hand, there is a large body of theoretical and empirical literature on the determinants of innovation persistence in firms (see Le Bas and Scellato 2014; and Crespi and Scellato 2015 for a summary of main findings). On the other hand, a similarly extensive body of research deals with local knowledge spillovers in innovation and their role for spatial concentration of innovation activities (see Audretsch and Feldman 2004; Carlino and Kerr 2015; Feldman and Audretsch 1999; Moreno, Paci, and Usai 2005a, 2005b; Simmie 2002; Thompson 2006). However, there is very little work that combines these two strands and examines the role of local knowledge spillovers for the persistence of innovation activity in firms. Bringing these two strands together can help to better understand the micro-foundations of regional concentration of innovative activities.

2.1. Determinants of innovation persistence in firms

Innovation in firms is characterised by three main features: it is costly, its outcome is uncertain, and it produces positive externalities (i.e. only a part of the returns from innovation can be appropriated by the innovator). In order to avoid malinvestment, firms usually aim at limiting innovation to activities that promise high returns and avoid activities that are too costly, too uncertain, and have too high externalities. As a result, firms may conduct innovation activities and introduce new products or processes only from time to time, leading to a perforated pattern of innovation activity over time.

Innovation persistence describes the dependence of a firm's decision to innovate in period t from the firm's innovation status in the previous period. The concept of innovation persistence denotes the ability and decision of firms to avoid this perforate pattern and either innovate or refrain from any innovation activity over a longer period of time (Peters 2009). 'Innovating' refers in this context to either providing inputs to innovation (i.e. conducting innovation activities, see e.g. Peters 2009) or to producing innovative output (e.g. new technological knowledge, see e.g. Geroski, van Reenen, and Walters 1997; Cefis 2003; or new products introduced on the market and new processes implemented in the firm, see e.g. Raymond et al. 2010; Clausen and Pohjola 2013).

Theoretical explanations of innovation persistence stress four main mechanisms that keep firms permanently in or out of innovation. First, fixed costs of innovation represent an entry barrier to innovation, especially for small firms with fewer resources at their disposal. Fixed costs include laboratory and equipment for research and development (R&D), and the hiring of specialised staff to perform innovation activities who cannot be used in other functional areas of a firm. In addition, part of this initial investment constitutes sunk costs and may prevent firms from entering but also from stopping innovation activities once started (Sutton 1991; Máñez et al. 2009; Peters 2009).

A second mechanism relates to the self-enhancing effect of innovating in the past on innovating in the future due to better financing opportunities. If firms were able to yield economic returns from prior innovations they will have additional resources for further investment in innovation ('success breeds success') (Flaig and Stadler 1994). As innovative firms on average are more successful than non-innovative ones (Geroski, Machin, and van Reenen 1993; Leiponen 2000; Cefis and Ciccarelli 2005; Love, Roper, and Du 2009), past innovation can provide the financial basis for future innovation.

A third mechanism stresses the role of 'learning-by-doing' for innovation persistence by referring to the fact that experience in innovating generates new knowledge that facilitates further innovation (Geroski, van Reenen, and Walters 1997). At the same time, firms without innovation activity in the past will have to invest substantially into acquiring the knowledge needed to set up and run innovation activities, which will prevent many firms from starting innovation.

Finally, innovation changes competition in markets, for example, by reducing price competition, shifting user preferences towards quality characteristics of products, or squeezing out non-innovative firms (Woerter 2014). These changes in market structure may stimulate further innovation. In the same vein, in markets that primarily consist of non-innovative suppliers, market structures will provide little incentives to engage in innovation, e.g. by offering small if any rents for innovators due to high price competition or a lack of users' willingness to pay for high-quality products.

2.2. Localised knowledge as a source for innovation persistence

A factor that has received relatively little attention in research on innovation persistency so far is a firm's local knowledge environment. Previous literature has mainly focused on the direct impact of the firm's local knowledge environment on innovation. The local knowledge pool may directly increase a firm's propensity to innovate by exploiting knowledge spillovers. The concept of knowledge spillovers describes positive externalities of knowledge that relate to the non-exclusive and non-rival use of knowledge (Arrow 1962), allowing firms to profit from knowledge produced by others (Breschi and Lissoni 2001). Spillovers lower the cost of innovation, e.g. by observing others' innovation activities and learning from the experience of others when pursuing innovation or by finding more easily qualified workers for conducting innovation activities. Since effectively absorbing external knowledge often requires close contact to the knowledge producer, knowledge spillovers tend to be localised (see Audretsch and Feldman 2004).

Localised knowledge can affect innovation persistence in two ways. First, as explained it may directly increase a firm's propensity to innovate in any period of time. As the local knowledge pool is unlikely to rapidly change over time, a positive impact in every period will contribute to a persistent innovation pattern.[1]

In addition to this direct effect, localised knowledge may have a second, indirect effect on innovation persistence by affecting true state dependence. This means that localised knowledge additionally influences ('moderates') the causal relationship of past on future innovation activities. The reason is that local knowledge spillovers can strengthen or soften the four basic mechanisms discussed above. As this moderating effect is in the centre of our analysis, we briefly discuss how localised knowledge can affect the four mechanisms that lead to true state dependence.

With respect to entry and exit barriers to innovation resulting from fixed and sunk cost of innovation, a large pool of local knowledge may reduce these costs leading to more entry and exit. Proximity to other knowledge sources reduces transaction costs and makes it easier to find suitable cooperation partners. This lowers the cost of firms for substituting internal knowledge resources with external ones, e.g. by outsourcing certain non-strategic activities in the innovation process. It also allows them to reduce in-house capacities for innovation (e.g. in terms of the size of the R&D department) and rely more on external knowledge. Having more innovation activities in the local environment may hence reduce innovation persistency as it eases entry to and exit from innovation.

Concerning the 'success breeds success' mechanism for persistency, a large pool of local knowledge can increase persistency. As firms depend on external inputs to successfully innovate, both in terms of receiving ideas for innovation and accessing knowledge to timely and efficiently complete innovation projects, a firm's local knowledge environment can be an important determinant for innovation success (Leiponen and Helfat 2011; Roper, Love, and Bonner 2017). One may expect that firms in a thick knowledge environment can more easily tap into the knowledge necessary to succeed in their innovation efforts and hence achieve better innovation results. This can be a 'success breeds success' mechanism of innovation persistency at the regional level, as successful innovation of one firm supports successful innovation of others. At the same time, firms located in a region with little external knowledge in their vicinity will find it more difficult to innovate successfully and may hence refrain from innovation activity, contributing to a high persistency of non-innovative firms.

A large pool of local knowledge will also facilitate learning in firms. Regular and face-to-face interaction with knowledge sources (other firms, universities, research institutes) eases the identification and absorption of knowledge relevant to a firm's innovation activities (Cohen and Levinthal 1990). A common background among actors that engage in knowledge exchange helps to build trust and a mutual understanding of the challenges faced in innovation activities, which can be crucial for identifying the right external knowledge needed to advance a firm's innovation efforts.

A concentration of knowledge sources and innovation activities within a region can also contribute to the emergence of a regional eco-system of innovation that shapes the market structures in which the region's innovative firms operate (Oksanen and Hautamäki 2014; Foray 2014). If market structures for all innovative firms in a region evolve towards a similar direction by strengthening the role of innovation for competition, this will provide additional incentives to stay on an innovation track.

In summary, a large stock of knowledge in a firm's region may result in higher innovation activities *and* a higher innovation persistency as knowledge thickness contributes to more successful innovations, facilitates learning from others' innovations, and changes market structures towards a higher importance of innovation as a competitive factor. At the same time, a lack of regional knowledge sources relevant to innovation in firms may work in the other direction and deter firms from innovating in a persistent way. However, there might also be a counteracting mechanism if a large stock of innovation-pertinent knowledge in a region decreases fixed and sunk costs of innovation, thereby reducing the barriers to entry into or exit from innovation activities.

2.3. Spatial scope of localised knowledge spillovers

A critical issue when analysing the role of a firm's knowledge environment is the spatial scope of knowledge spillovers. Empirical studies of the distance decay of knowledge for innovation found different results. Wallsten (2001) studied participation in the Small Business Innovation Research programme in the U.S. and found that firms are more likely to receive a grant if their neighbours within a 1/10 of a mile received a grant. The effect rapidly diminishes with increasing distance and disappears by 5 miles. Baldwin et al. (2008) found for Canadian manufacturing firms that knowledge spillovers are significant over a distance of 10 kilometres. Rammer, Kinne, and Blind (2020) found that the impact of local public knowledge sources (universities, research institutes) on firms' innovation in an urban environment diminishes already after some 100 metres. Buzard et al. (2020) used patent citation data for American R&D labs and showed that knowledge spillovers are strongest over distances up to 5 miles. Funke and Niebuhr (2005) analysed knowledge spillovers based on the relationship between regional productivity and R&D activity in West German planning regions. They found that the intensity of spillovers declines by 50% over a 23 kilometres distance. These results suggest highly localised knowledge spillovers at relatively small geographical scales (see also Rosenthal and Strange 2003, 2008; Murata et al. 2014)

At the same time, the literature on the geography of knowledge flows stresses the importance of inter-regional and international knowledge (Bathelt, Malmberg, and Maskell 2004; Gertler and Levitte 2005). Niosi and Zhegu (2005) argue in the case of aerospace clusters that knowledge spillovers are much less spatially constrained. Bottazzi and Peri (2003) analysed the impact of R&D spending on the output of new ideas in European Regions and found spillovers that extend within a distance of 300 kilometres. Nevertheless, as Bathelt, Malmberg, and Maskell (2004) argued, the local learning process and the channels to access external knowledge cannot be viewed separately. Although codified knowledge is in principle not proximity-constrained, it usually needs to be used together with locally transferred tacit knowledge to create new knowledge. Thus, the use of global or non-local knowledge is closely linked to the use of local knowledge (Bathelt and Cohendet 2014).

In addition, the type of sector in which a firm operates may also affect the spatial scope of localised knowledge spillovers. Separating between manufacturing and services is critical in this respect as the nature of products (tangible vs. intangible), the characteristics of innovation (technology-based vs. based on learning and interaction), and the relevance of external knowledge often differs (Ettlie and Rosenthal 2011; Hsieh et al. 2018; Love, Roper, and Bryson 2011; Tavassoli 2018). This also affects the type and role of knowledge spillovers for innovation. Innovation in manufacturing is more strongly based on tangible technologies and their combination with digital approaches (e.g. software applications). The underlying technological knowledge can easily be codified, e.g. through patents, software codes or technical documents. In services, innovation usually includes a strong intangible component, particularly with respect to skills and competencies of employees who deliver novel services, and the interaction between users and service providers. Critical knowledge for such innovations is much more difficult to codify and often requires personal interactions and learning by individuals. One may hence expect that the role of knowledge spillovers for innovation diminishes much faster in services the more distant knowledge is.

2.4. Empirical studies on local knowledge spillovers and persistence of innovation

Only few studies have investigated the link between localised knowledge and persistence of innovation in firms. The study most closely related to our work is Tavassoli and Karlsson (2018). They use data of 574 firms from five waves of the Community Innovation Survey in Sweden between 2002 and 2012 and apply a dynamic random effects probit model to analyse persistency in the introduction of product, process, organisational and marketing innovation in different regional settings. They split the sample of firms in three categories based on tercile values for total regional employment, knowledge-intensive regional employment in services, and total number of innovative firms in the functional region. Their results show that firms in regions with thicker labour markets and with a greater number of innovative firms tend to have a higher probability of being persistent innovators, but no clear differences are found for regions with different levels of knowledge intensive service employment.

Other studies have used measures on regional innovation that are only weakly linked to the concept of knowledge spillovers. Nam and Bao Tram (2021) compared the innovation and export persistence of Vietnamese SMEs in provinces with a high and low regional competitive index, respectively, and claimed that persistence is higher in weaker business environments. Using a sample of Italian manufacturing firms, Antonelli, Crespi, and Scellato (2013) found a significant role of the regional context for total factor productivity persistence. They argue that productivity persistence reflects persistence of innovation activities. Holl and Rama (2016) found that firms located in the Spanish Basque country were more likely to persist in their innovative activities during the 2008 crisis than firms located in other regions like Catalonia or Madrid. This regional effect is attributed to the relative strength of the Basque Regional Innovation System. Cruz Castro et al. (2018) further investigated the abandonment of in-house R&D in Spanish firms since the onset of the economic crisis and also stressed significant regional heterogeneity. Also for Spanish firms, Holl (2021) found that the regional business expenditure on R&D is positively related with a more continuous self-reported commitment to innovation of innovation active manufacturing firms.

2.5. Hypotheses

Based on the literature discussed above, we derive four hypotheses that will guide our empirical research. Following the arguments put forward in section 2.2, we expect that firms with a thick local knowledge environment, i.e. with many other actors in their vicinity producing new knowledge that is relevant to the firms' innovation activities, will be more likely to innovate, while firms surrounded by very few relevant knowledge sources will be less likely to innovate because they benefit less from knowledge spillovers. The first hypothesis refers to this direct effect of localised knowledge on innovation:

H1: A larger pool of local knowledge positively contributes to conducting innovation.

In addition, we expect the localised knowledge to increase true state dependence as a source of innovation persistence. The existence of a large pool of relevant knowledge around a firm is likely to reinforce the main mechanisms leading to true state dependence, meaning that the effect of past innovation on current innovation becomes stronger. The second hypothesis refers to this moderating effect of localised knowledge on persistence:

H2: A larger pool of local knowledge positively moderates true state dependence as source of innovation persistence in firms.

The main mechanism behind the likely impact of local knowledge stocks on a firm's innovation persistence is the transfer of knowledge between local knowledge sources and the firm. While this transfer may be intended or unintended from the source's point of view, the discussion in section 2.3 stressed the role of geographic proximity for the transfer to happen, based on personal contacts between the knowledge source and the firm. As personal contacts become more expensive and more complicated (and thus less frequent) the larger the distance between the firm and a knowledge source is, it is likely that the contribution of surrounding knowledge sources to innovation persistence diminishes by distance. The third hypothesis hence reads:

H3: The effect of local knowledge spillovers on innovation persistence diminishes by spatial distance.

Our final hypothesis is related to industry heterogeneity with respect to manufacturing and services. As discussed above, the more intangible and tacit nature of knowledge in services and the fact that innovation is more often based on learning from others based on personal interaction make it more likely that highly localised knowledge is more important for innovation persistence in services sectors compared to manufacturing, and that the effect of knowledge spillovers diminishes much faster as distance to the knowledge source increases. The fourth hypothesis hence reads:

H4: The effect of local knowledge spillovers on innovation persistence is more localised (i.e. spatially more confined) in services.

3. Data and descriptive results

3.1. Data

We use data from the Mannheim Innovation Panel (MIP), which provides information regarding the innovation behaviour of German firms. The MIP data set is based on the annual German Innovation Survey carried out by the Centre for European Economic Research (ZEW) in Mannheim on behalf of the German federal government (Peters and Rammer 2013). The MIP panel is representative for the population of German firms with 5 or more employees in manufacturing, mining, energy and water supply, wholesale, transportation, information and communication, financial as well as other business-related services. We restrict our analysis to manufacturing and service sector firms. Every second year it is the German contribution to the European-wide Community Innovation Surveys (CIS).

We use MIP data for the period 2002–2016, which provides us with panel information for about 29,611 different firms, including firm location at the ZIP-code level. However, since participation in the MIP survey is voluntary, not all firms necessarily responded in consecutive years and not all firms responded always to all questions. Thus, we end up with an unbalanced panel of nearly 15,398 firms (8,433 manufacturing firms and 7,275 service sector firms, among them 310 firms switching industries over the time period) and 66,402 firm-year observations. The average number of consecutive observations per firm of is 4.3 years. About 49% of our sample firms remain 3 and more consecutive years in the sample and 21% more than 6 consecutive years. After accounting for the initial observation and taking lags, the econometric analysis makes use of 45,858 observations, 25,556 in manufacturing and 20,302 in services. Table A1 to A3 in the Appendix provide information on the characteristics of the original MIP sample and our estimation sample regarding their sectoral distribution, their size distribution and the observed innovation behaviour. Overall, our estimation sample reflects the original sample characteristics quite well and does not raise any obvious selectivity concerns.

3.2. Innovation and knowledge indicators

Following Peters (2009), we measure innovation persistence based on innovation input.[2] Specifically, we use firms' financial expenditure for activities that aim at developing and implementing new products or processes. Hence, our dependent variable innovation, $Inno_{it}$, equals 1 if firm i is engaged in innovation activities in year t, measured here as having innovation expenditure larger than zero in year t. Persistence in innovation activities occurs if a firm that conducts innovation activities in year $t-1$ ($Inno_{it-1} = 1$) also undertakes innovation activities in the following year ($Inno_{it} = 1$).

We refrained from using innovation output indicators for two reasons: First, in innovation surveys such as the CIS, output indicators usually refer to a three-year reference period, i.e. they capture whether a firm has introduced a new or improved product or a new or improved process within the previous three-year period. This definition causes overlaps in the dependent variable in the panel data setting that would bias estimates for innovation persistence (Peters 2009). In contrast, the information on innovation expenditure is available on a yearly basis. Secondly, a firm can decide on whether to invest in innovation, but it cannot decide of succeeding with innovation as the latter depends on a number of factors out of a firm's control, e.g. competitors' actions or market acceptance (see also Arqué-Castells 2013).

To examine the role of local knowledge spillovers for innovation persistence, we use patent data from the European Patent Office (EPO). Although we view knowledge spillovers in a wider sense than just patentable technological knowledge, we have to accept that directly observing all kinds of knowledge flows is notoriously difficult, particularly if one wants to measure spillovers for a large number of firms on a fine-grade geographic scale. Patent information allows to both locate knowledge sources and to assess the relevance of this knowledge for each firm. We derive our knowledge spillover measure *KnowPool* through a three-stage procedure described in detail in the Appendix. We exploit the patent information for patent classes to relate technology relevant patents to 4-digit industries and at the 5-digit ZIP code ('postal area') level to calculate our patent measure within discrete distance thresholds of 5, 10, 20, 30, and 50 kilometres.

3.3. Descriptive statistics

Table 1 shows the transition probabilities for the dependent variable *Inno*. We compare firms in locations with a weak local knowledge environment with firms in locations with a strong local knowledge environment. The local knowledge environment is proxied here as the number of three-year lagged patent applications within a 5 kilometres distance threshold. Locations with a weak local knowledge environment are those with a low patenting activity (lowest quartile of the distribution of *KnowPool*), while locations with a strong local knowledge environment correspond to the highest quartile of patenting activity.

Innovation is permanent to a large extent, but there are clear differences between firms located in areas with high patenting activity versus those firms located in areas with a low patenting activity. Based on the 5 kilometres distance threshold, we observe that in areas with a patenting activity in the upper quartile, nearly 87% of innovators in one year persisted in innovation in the subsequent year. In contrast, in areas with a low patenting activity, firms' innovation persistence is considerably lower. In those areas, 75% of innovative firms continued to spend on innovation in the next year. There are also some notable differences between manufacturing and services. In general, persistence in innovation is higher in manufacturing, but in both sectors firms in areas with a higher patenting activity show a higher persistence than firms in low-patenting areas. The difference in persistence is nearly 8 percentage points in manufacturing and about 17 percentage points in services. However, the picture is reversed for non-innovators. Non-innovator status is slightly more persistent in areas with low patenting activity – particularly in the service sector.[3] This suggests that there is indeed a positive link between the local knowledge environment and innovation persistence.

Looking at the length of innovation spells, survival analysis also points to a role of the local knowledge environment for innovation persistence as we again observe marked differences between firms in areas surrounded by a high versus a low patenting activity. Figure 1 shows the innovation survival rates for manufacturing and service sector firms located in the upper quartile versus the lower quartile of patent activity within a distance of 5 kilometres.[4] Firms in areas with a high patenting activity demonstrate higher survival rates in innovation. The log-rank test shows that the difference between the survivor functions is significant at the 1% level.

The observed higher innovation persistence in areas with a strong local knowledge environment may be driven by differences in the spatial distribution of firms with different characteristics. For example, larger firms tend to have higher innovation persistence, and if larger firms tend to locate in areas with a stronger knowledge environment, one would observe higher persistence without necessarily implying that there are local knowledge spillovers in place that facilitate innovation persistence. In addition to observable firm characteristics, there could also be a range of unobserved firm characteristics driving the observed pattern and that need to be accounted for in the econometric analysis.

4. Econometric model and estimation approach

4.1. Econometric model

Our empirical model is based on a simple model of optimisation for a firm facing the decision to invest in innovation. A profit maximising firm engages in innovation if the expected present value of profits (benefits minus costs) from investing in innovation $Inno_{it}^{*}$ is positive. This does not

Table 1. Transition probabilities in areas with high and low patenting activity (based on 5 kilometres distance band patent counts, in percent).

		All sample firms		Manufacturing		Services	
Local patenting activity		NON-INNO	INNO	NON-INNO	INNO	NON-INNO	INNO
Lowest quartile	NON-INNO	89.2	10.8	87.2	12.8	90.6	9.4
	INNO	24.7	75.3	17.1	82.9	39.0	61.0
Highest quartile	NON-INNO	85.9	14.1	85.6	14.5	86.3	13.7
	INNO	13.4	86.6	9.3	90.7	21.6	78.4

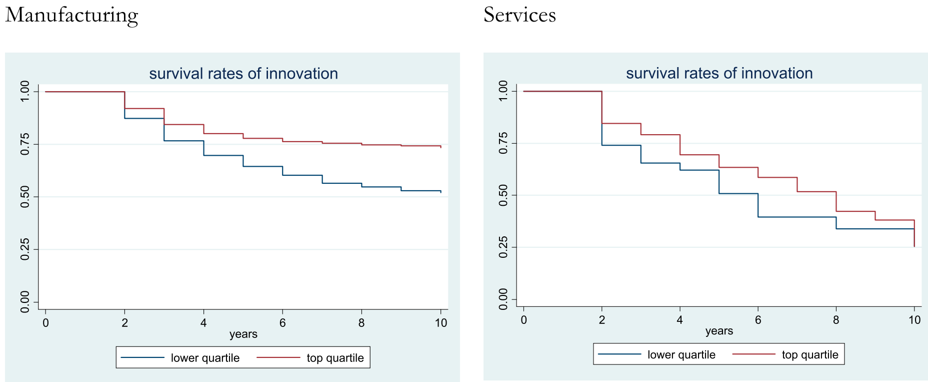

Figure 1. Survival rates of innovation (%) in firms in areas with high versus low patenting activity.

Notes: The graph shows Kaplan-Meier survival estimates of innovation behaviour in firms differentiated by the size of the local knowledge pool. Lower and top quartile defines locations below the 25th and above the 75th percentile of patent activity within a distance of 5 kilometres.

imply that a firm has to be profitable in t as firms may decide to invest in innovation in order to overcome a situation of low profitability (see Manzaneque et al. 2020).

$Inno^*_{it}$ depends on past realised innovation $Inno_{it-1}$ for the four reasons outlined above. On the one hand, firms with past innovation have already incurred start-up (sunk) costs, for instance for setting up an R&D lab, which reduces future innovation costs, and on the hand, past innovation increases the expected benefits of future innovations due to success breeds success, learning effects, or innovation-supportive market structures. These arguments imply that the probability of engaging in innovation in the current period will depend on the decision to innovate in past periods. In equation (1) below, these effects are captured by θ that is our measure for true state dependence, which is a source of innovation persistence. It is therefore important to account for dynamic effects in the econometric model. In addition, expected profits from innovation also depend on a number of observed firm-specific attributes x_{it} as well as a number of time-invariant firm-specific characteristics φ_i that cannot be directly observed (for instance, characteristics of the products or managerial ability). Lack of control for these unobserved characteristics is known to lead to a 'spurious' state dependence in dynamic models (see Heckman 1991), and as a result to biased estimates of any explanatory variable potentially correlated with it. In summary, the expected profits due to innovation can be written as:

$$Inno^*_{it} = \theta Inno_{it-1} + \beta x_{it} + \varphi_i + \varepsilon_{it}. \tag{1}$$

ε_{it} captures time-varying idiosyncratic error shocks. It is assumed that the conditional distribution of ε_{it} is i.i.d. $N(0, 1)$. Unfortunately, we do not observe the expected present value of profits from investing in innovation, but instead we observe whether the firm is engaged in innovation activities or not. Consequently, the innovation status of firm i in period t can be expressed by the binary indicator $Inno_{it}$:

$$Inno_{it} = \begin{cases} 1 & \text{if } Inno^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Due to the assumption that ε_{it} follows a normal distribution, the probability of investing in innovation can be written as:

$$Pr(Inno_{it} = 1 | x_{it}, Inno_{it-1}, \varphi_i) = F(\theta Inno_{it-1} + \beta x_{it} + \varphi_i), \tag{3}$$

where $F(\cdot)$ is the normal cumulative distribution function.

We express the unobserved heterogeneity φ_i as a function of time-averages of all the explanatory variables $\bar{x}_i$ (except the lagged endogenous variable) (Chamberlain 1980). Another important issue refers to the 'initial conditions problem' as the initial period of observation in the sample does not correspond with the first period the firm is in the market. The beginning of the process is unobserved, but presumably the unobserved effects depend on the initial observation. Adopting the Wooldridge (2005) approach, we model the unobserved heterogeneity conditional on the initial condition, $Inno_{i0}$, and the time-averages of the exogenous variables.

$$\varphi_i = \partial_0 + \partial_1 Inno_{i0} + \partial_1 \bar{x}_i + \vartheta_i, \tag{4}$$

where ϑ_i is also normally distributed and independent from $\bar{x}_i$ and $Inno_{i0}$.[5] This reduced form can be plugged into equation (3). The model, also called correlated random effects probit model, then has the same structure as the standard random effects probit, except that the explanatory variables are given by x_{it}, $Inno_{it-1}$, $Inno_{i0}$ and $\bar{x}_i$.[6]

4.2. Estimation Approach

The key question of our paper is how the local knowledge environment moderates firms' innovation persistence. For this purpose, we include the knowledge pool that is relevant to firm i at time t located in region l, $KnowPool_{it}^{l}$, and its interaction term with the lagged innovation status $Inno_{it-1}$.[7] In the empirical analysis, we measure $KnowPool_{it}^{l}$ by the technology-relevance weighted three-year lagged flow of patent applications in different distance bands as described in the Appendix. The augmented latent model is then given by,

$$\begin{aligned} Inno_{it}^{*} = & \beta x_{it} + \theta Inno_{it-1} + a_1 KnowPool_{it}^{l} \\ & + \alpha_2 (Inno_{it-1} * KnowPool_{it}^{l}) + \partial_0 + \partial_1 Inno_{i0} + \partial_1 \bar{x}_i + \vartheta_i + \varepsilon_{it}. \end{aligned} \tag{5}$$

Our main parameters of interest is the coefficient of the interaction term, α_2. $\alpha_2 > 0$ implies that a larger pool of local knowledge positively moderates the relationship of lagged innovation on current innovation and therefore increases true state dependence as source of innovation persistence in firms (H2). α_1, in contrast measures the direct effect of the knowledge pool on the decision to innovate (H1).

The main virtue of this approach is that it accounts for the correlation between $Inno_{it-1}$, $KnowPool_{it}^{l}$ and φ_i. This is particularly important in the present case since the initial (and usually time-invariant) firm location is potentially correlated with innovation status. Firms with unobserved characteristics that are positively linked with innovation activity may be attracted to regions that offer better conditions for innovating.

Firm level controls: In line with previous theoretical and empirical studies on innovation, we control for firm size (measured as the log of the number of employees). Firm size constitutes an important determinant in many studies on innovation persistence (e.g. Peters 2009; Raymond et al. 2010; Clausen et al. 2012; Ganter and Hecker 2013; Hecker and Ganter 2014), as a minimum of resources is required to fund innovation activities.

Furthermore, we control for the age of firms (log of years since the firm was created), whether the firm sells on international markets, and whether the firm belongs to an enterprise group. As reviewed by Le Bas and Scellato (2014), several previous studies have also included these controls. Firm age is a proxy for knowledge accumulation. Firms that operate in international markets are likely to have greater organisational capabilities, larger competitive pressure, but also larger benefits from innovation due to larger market size and technology sourcing, making them more likely to innovate (Peters, Roberts, and Vuong 2018). Firms belonging to a group are more likely to innovate as they may also benefit from within-group knowledge spillovers (Raymond et al. 2010) as well as resources that help to sustain innovation efforts. In all our estimations, we use one-year lagged values of the firm-specific control variables.

Sectoral and regional controls: Previous research has furthermore shown that persistence varies across industries. Our specification therefore includes 2-digit Nace sector dummies. As regional controls, we include population density, area, and the GDP per employed at the district level, which is a spatial division based on commuter flows and corresponds to the NUTS[8] 3 level. For the former two variables, we also include the quadratic term to allow for nonlinearities. Finally, we also include NUTS 2 regional dummies to control for other potentially remaining unobserved fixed region-specific factors that could influence persistence in innovation.

5. Estimation results

5.1. Benchmark results

Table 2 shows how the local knowledge environment affects the persistence of innovation in manufacturing. Displayed are marginal effects and clustered standard errors of our benchmark model, the correlated random effects probit model specified in equation (5), for firms in manufacturing. In column (1), the external knowledge pool captures the number of firm-specific technology-relevant patent applications (in year *t-3*) within a threshold of 5 kilometres. In column (2) to (5), we gradually increase the spatial scope up to 50 kilometres.

Our results do not show a significant direct effect of the local knowledge pool $KnowPool_{it}^{l}$ on the probability to engage in innovation activities, except for our largest distance threshold for which we find a weakly significant positive coefficient. Therefore, we have to reject H1 in case of manufacturing. It seems that manufacturing firms reach out far beyond their local area for obtaining relevant knowledge for innovation. This may reflect the situation that many manufacturing firms in Germany are highly specialised on certain products and technologies, and relevant knowledge for innovating in such specialised fields requires searching nation-wide or even globally.

As in previous research (Peters 2009), we corroborate evidence for true state dependence in firms' innovation activities. An innovator in $t-1$ has a significantly higher probability of innovating in year t than a non-innovator even after controlling for observed and unobserved characteristics. Across different specifications, we estimate this difference to be between 47 and 52 percentage points which is even slightly higher than comparable estimates for the period 1994–2002 (Peters 2009). Given that the unconditional difference is around 70–76 percentage points (see Table 1), we can conclude that about 2/3 of the persistence in innovation is due to true state dependence, while the rest is explained by observed and unobserved characteristics. ρ indicates the importance of individual heterogeneity. About 27% of the unexplained variation of innovation can be attributed to individual heterogeneity. Also in line with previous studies, we find a highly significant initial condition indicating a substantial correlation between firms' initial innovation status and the unobserved heterogeneity.

The key variable of interest is the interaction term of the local knowledge pool with the lagged innovation status, $Inno_{t-1} \times KnowPool_{it}^{l}$, to measure how the local knowledge environment moderates innovation persistence. While the knowledge pool itself does not turn out to be significant in manufacturing, the interaction term matters, with its size and significance falling in distance; thus providing support for our hypotheses H2 and H3. In column (1), the distance threshold is up to 5 kilometres from the postal code centroid of the focal firm. The interaction term is positive and highly statistically significant at the 1% level. The estimated interaction term is 0.010. This positive interaction with the lagged innovation status confirms that persistence is indeed higher for firms in areas with more patenting activity (H2). Figure 2 illustrates the interaction effect between past innovation status and knowledge pool graphically. The top left graph shows the predicted innovation probability (with 95% confidence intervals) for lagged innovators and non-innovators as a function of different levels of the local knowledge pool, defined as patent activity within a distance of 5 kilometres. Interestingly, the predicted innovation probability increases with increasing knowledge pool for past innovators while it decreases for past non-innovators. This results from the negative (non-significant) effect of the knowledge pool variable. This finding suggests that an increasing local knowledge pool tends to discourage non-innovators from starting innovation activities, while it encourages innovators to remain innovative.[9] In addition, the bottom left graph presents the conditional marginal effect (with 95% confidence intervals) of the past innovation status, calculated

Table 2. Manufacturing: Marginal effects of correlated random effects probit estimations.

	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20km	(4) Up to 30 km	(5) Up to 50km
$Inno_{t-1}$	0.506***	0.487***	0.480***	0.471***	0.456***
	(0.024)	(0.022)	(0.021)	(0.019)	(0.018)
KnowlPool	−0.003	−0.003	0.001	0.003	0.006*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$Inno_{t-1}$*KnowlPool*	0.010***	0.009**	0.010**	0.009**	0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Size	0.027	0.027	0.027	0.028	0.027
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Age	−0.010*	−0.010*	−0.010*	−0.010*	−0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Group	−0.023	−0.023	−0.024	−0.024	−0.023
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)
Export	0.073***	0.075***	0.074***	0.074***	0.075***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Inno_0	0.279***	0.281***	0.281***	0.282***	0.283***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Mean(Size)	0.039*	0.039*	0.038*	0.038*	0.039*
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Mean(Group)	0.031	0.032	0.033	0.033	0.032
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)
Mean(Export)	0.074***	0.073***	0.073***	0.074***	0.074***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Regional controls (NUTS3)					
Population density	0.010	0.012	0.007	0.007	0.009
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Area	−0.009	−0.009	−0.011	−0.011	−0.010
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
GDP per employed	0.032	0.034	0.026	0.023	0.029
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Region fixed effects (NUTS2)	Y	Y	Y	Y	Y
Sector fixed effects (Nace2)	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
σ_v	0.615	0.617	0.618	0.618	0.618
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
ρ	0.275	0.276	0.276	0.277	0.276
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	25,556	25,556	25,556	25,556	25,556
Groups	8433	8433	8433	8433	8433
Log likelihood	−8395	−8400	−8397	−8396	−8399

Notes: Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year *t*− *3* (patent flow approach) within the different distance thresholds. Clustered standard errors are reported in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% levels. Population density and area are included each as a second-order polynomial in the estimation. While some of the estimated polynomial coefficients are weakly significant, the combined overall marginal effect turns out to be insignificant.

as the change in the predicted innovation probability between lagged innovators and non-innovators for different levels of the local knowledge pool. We observe that for all levels of the knowledge pool, the marginal effect of the past innovation status is significantly larger than the red horizontal line at zero, representing no difference in the innovation probability between the two levels of lagged innovation, i.e. no persistence. Furthermore, the graph shows that the persistence effect is increasing in the level of the local knowledge pool. Overall, our findings provide evidence that the local patenting environment is moderating firms' true state dependence and that local knowledge spillovers contribute to firms' innovation persistence.[10] Our results therefore provide empirical support to the argument put forward by Castellani (2017) that strong local knowledge flows can lead to persistence in innovation activities. Our results are also consistent with the findings in Tavassoli and Karlsson (2018), who observe higher persistence for product and process innovations in regions with a greater number of innovative firms, and with Holl (2021), who finds that regional R&D business expenditure raises firms' commitment to innovation.

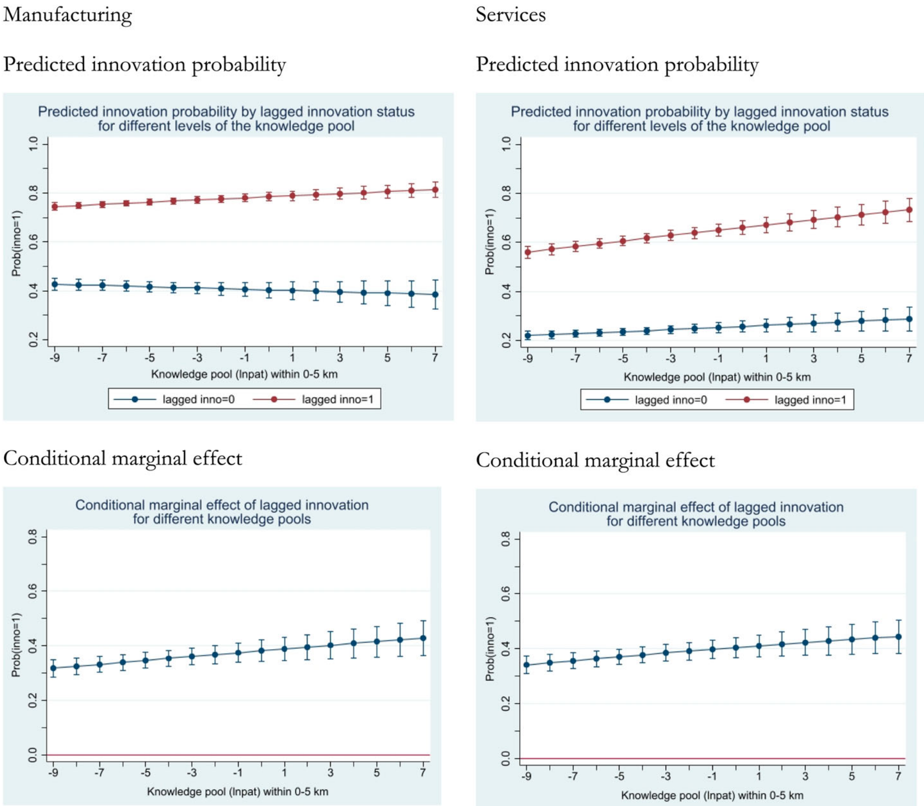

Figure 2. Predicted innovation probability and conditional marginal effects by lagged innovation status and local knowledge pool.

Notes: The top graphs show the predicted innovation probability (with 95% confidence intervals) for lagged innovators and non-innovators as a function of different levels of the local knowledge pool, defined as patent activity within a distance of 5 kilometres. The knowledge pool range is based on the observed minimum (−9.210) and maximum (6.771) in the estimation sample, with the median at −5.465 and the 95% percentile at 2.444. The bottom graphs present the conditional marginal effect (with 95% confidence intervals) of lagged innovation, calculated as the change in the predicted innovation probability between lagged innovators and non-innovators for different levels of the local knowledge pool. For all levels of the knowledge pool, the marginal effect is larger than the red horizontal line at zero, representing no difference in the innovation probability between the two levels of lagged innovation, i.e. no persistence. Results are based on estimation results in column (1) of Table 2 and 3 for manufacturing and services, respectively.

In column (2), we widen the distance band up to 10 kilometres. The interaction term continues to be positive and of similar magnitude, but is of somewhat weaker significance (i.e. significant at the 5 percent level). In column (3), we extend the distance threshold up to 20 kilometres and in column (4) to 30 kilometres. The interaction term remains similar and is also significant at the 5 percent level. Beyond the 30 kilometres threshold, we observe that the interaction term drops in magnitude and loses significance. This suggests that spillovers that contribute to innovation persistence in manufacturing tend to fall by distance (H3) and are spatially constrained within 30 kilometres. This finding is similar to Cainelli and Ganau (2018), who found in the Italian context positive localisation economies up to a 30 kilometres distance threshold. It is also consistent with the geographical extent of R&D spillovers found in Funke and Niebuhr (2005) for West German regions.

Table 3 and Figure 2 (right side) show the corresponding results for the service sector. Innovation in services is highly state dependent, and state dependence shows a similar magnitude as in manufacturing. In contrast to manufacturing, the local knowledge pool $KnowPool_{it}^{l}$ is significant up to 10 kilometres, indicating a positive influence of the local patenting activity on the probability of engaging in innovation activities in services (H1). This different result may be linked to the fact that knowledge spillovers contributing to the probability that a firm engages in innovation activities in services are spatially more constrained, that there may be more service firms with a similar technological focus within the same region, and that the relevant knowledge for innovation in services is less specific than it is in manufacturing (e.g. often building upon information and communication technologies).

The interaction term of $KnowPool_{it}^{l}$ and $Inno_{t-1}$ is significant up to the 20 kilometres distance threshold, indicating that in services too, the local knowledge environment moderates innovation persistence (H2). The effect is also falling by distance (H3) and it is even somewhat spatially more constrained. Beyond 20 kilometres, we do not observe a significant impact of the local patenting environment on innovation persistence in services. This shows that innovation persistence in the service sector benefits from a local knowledge pool at relatively short distances, while the probability of being innovative is influenced by the local knowledge pool over an even shorter distance. Compared to manufacturing, these results highlight that local knowledge spillovers that contribute to persistence are even more localised in services. The shorter distance of spillover effects in services

Table 3. Services: Marginal effects of correlated random effects probit estimations.

	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20km	(4) Up to 30 km	(5) Up to 50km
$Inno_{t-1}$	0.525***	0.515***	0.501***	0.497***	0.491***
	(0.023)	(0.021)	(0.019)	(0.017)	(0.016)
KnowlPool	0.007***	0.004***	0.000	0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Inno_{t-1}$*KnowlPool*	0.007**	0.007**	0.007*	0.006	0.004
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Size	0.017	0.017	0.017	0.018	0.018
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Age	−0.031***	−0.031***	−0.032***	−0.032***	−0.032***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Group	−0.006	−0.007	−0.006	−0.006	−0.006
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Export	0.012	0.013	0.013	0.013	0.013
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
$Inno_0$	0.241***	0.241***	0.243***	0.244***	0.244***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Mean(Size)	0.029	0.027	0.026	0.026	0.026
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Mean(Group)	0.055*	0.057*	0.057**	0.057**	0.057**
	(0.029)	(0.029)	(0.039)	(0.029)	(0.029)
Mean(Export)	0.126***	0.129***	0.133***	0.133***	0.134***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
Regional controls (NUTS3)					
Population density	−0.004	−0.001	0.006	0.007	0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Area	0.005	0.005	0.006	0.007	0.007
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
GDP per employed	0.017	0.016	0.023	0.025	0.028
	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)
Region fixed effects (NUTS2)	Y	Y	Y	Y	Y
Sector fixed effects (Nace2)	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
σ_v	0.519	0.518	0.521	0.522	0.521
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
ρ	0.212	0.211	0.213	0.214	0.214
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
Observations	20,302	20,302	20,302	20,302	20,302
Groups	7275	7275	7275	7275	7275
Log likelihood	−8068	−8074	−8079	−8080	−8081

Notes: Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year $t-3$ (patent flow approach) within the different distance thresholds. Clustered standard errors in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% levels. Population density and area are included each as a second-order polynomial in the estimation. While some of the estimated polynomial coefficients are weakly significant, the combined overall marginal effect turns out to be insignificant.

is in line with our hypothesis H4 and may indicate the greater importance of face-to-face based contacts for exchanging knowledge in services, reflecting the more tacit nature of knowledge that is critical for service innovations.

Overall, our novel findings on how local knowledge pools shape innovation persistence depending on distance expand previous studies on the geography of innovation that have stressed the role of knowledge spillovers and that they are bounded in space.

5.2. Robustness Analysis

In section 2.3, we discussed previous literature on the spatial scope of localised knowledge spillovers, which on the one hand shows a decay effect of distance in the diffusion of knowledge spillovers and on the other hand stresses the importance of inter-regional and international knowledge spillovers. However, these studies have not specifically addressed persistence. Our results so far confirm a decay effect of distance and suggest that spillovers tend to be spatially constrained in terms of their moderating impact on innovation persistence. We check the robustness of our results and estimate the model also for a 100 kilometres and 250 kilometres threshold.[11] The results are reported in Table A.4 in the Annex. Neither in manufacturing nor in services can we find a significant moderating impact of the local patenting environment on innovation persistence when we use more distant thresholds of 100 and 250 kilometres, respectively. These results confirm our thresholds reported in Tables 2 and 3, i.e. we find significant spillover effects on innovation persistence at relatively short distances of up to 30 kilometres in manufacturing and up to 20 kilometres in services.

In the literature on the persistence in innovation activities, it is common to use a one-year lag to measure persistence. However, given that it often takes time to complete innovation projects, our one-year lag in the innovation expenditure variable is likely to capture to some extent the effect of multi-year innovation projects. We check the sensitivity of our results by estimating persistence in innovation activities using two- and three-year lags instead. Table A.5 in the appendix reports the results, which corroborate our benchmark findings. That is, innovation activities are highly persistent also using two- and three-year lagged innovation indicators, although not surprisingly at a somewhat lower level. More importantly, we confirm that local knowledge positively moderates persistency in innovation activities and that the contribution to innovation persistence attenuates with increasing distance. We even find the same thresholds within which the local knowledge environment matters for innovation persistence using longer time lags.

6. Conclusions and discussion

This paper analysed the role of a firm's local knowledge environment for the persistence of the firm's innovation activities. We employed panel data of a representative sample of manufacturing and service firms in Germany, geo-coded at the ZIP level, and covering a period of 15 years. The local knowledge pool is measured by the number of patents in the vicinity of the firm that are relevant for the firm based on the firm's technology focus. We use different distance thresholds to analyse the geographic reach of local knowledge spillovers. Our results show that local knowledge affects innovation in two ways. First, a greater pool of relevant technological knowledge around a firm significantly increases the probability of conducting innovation activities as far as services are concerned. We do not find such a knowledge pool effect for manufacturing firms, however. This result suggests that localised knowledge pools ('knowledge clusters') – at least in the case of Germany – are mainly driving innovation in services, which is an important finding for regionalised innovation policies. In Germany, these policies often focus on regional clustering and networking among manufacturing firms while putting less emphasis on services (Kiese 2019; Falck, Heblich, and Kipar 2010).

More important than the direct effect of localised knowledge on a firm's decision to innovate is the indirect effect on innovation persistence via enforcing true state dependence. We find that firms within a rich knowledge environment are ceteris paribus less likely to change their innovation status compared to firms with a small knowledge pool around them. This moderating effect of localised knowledge on innovation persistence holds for manufacturing and services, but seems to be spatially more constrained in services. The effect holds up to 30 kilometres in manufacturing but only up to 20 kilometres in services.

Our findings contribute to the existing literature on knowledge spillovers and innovation in several ways. First, they add an explanation of why centres of innovation tend to maintain their innovation advantage and remain innovation hot spots over time (for recent evidence see Castellani 2017 for OECD regions; Rammer and Schubert 2018 for Germany; and Kerr and Robert-Nicoud 2020 for the U.S.). This finding is important for regional policy as it stresses a specific firm-level mechanism that can explain the widening of spatial disparities in innovation performance. It is in line with the studies cited above, which show that over the last decades regions with already higher patenting activity have indeed increased their rate of innovation and left behind other regions. Our findings clearly support approaches of building local clusters of innovative activities in certain industries in order to encourage networks among innovative firms for exchanging knowledge (see Tödtling and Trippl 2005; Bergman and Feser 1999). Our results also challenge policies that aim at reducing regional disparities by supporting innovation in firms in lagging regions. If such policies were not combined with developing a strong knowledge base for these firms, they may be less effective and may fail to dissipate innovation inequalities.

Secondly, we contribute to the ongoing debate on the geographic scope of knowledge flows (Breschi 2011). While many studies pointed to the fact that knowledge spillovers are geographically constrained (see Audretsch and Feldman 1996b; Ganguli, Lin, and Reynolds 2020; Alcácer and Chung 2007; Baptista and Swann 1998; Bottazzi and Peri 2003; Jaffe, Trajtenberg, and Henderson 1993), there exists yet no consensus on their actual geographic scale. Our results suggest that the geographic reach of knowledge spillovers is rather short, vanishing at around 30 kilometres. This result relates to the specific geographic situation in Germany, however. As a federal state that lacks a single dominating economic centre, innovation (as many other economic activities) tends to be more dispersed, both with respect to the location of innovative firms and other knowledge sources such as universities and research centres. This enhances the possibilities for firms to find a multitude of relevant knowledge sources within rather short distances.

Thirdly, our results show that local knowledge spillovers work differently in manufacturing and services, as such spillovers tend to be geographically more constrained in services. We relate this finding to the different nature of innovation in services (Ettlie and Rosenthal 2011; Love, Roper, and Bryson 2011). Service innovation often requires learning and interacting with (potential) users and demands types of knowledge that are more difficult to codify and transfer without personal communication than technological knowledge often used in manufacturing innovation. Though our measure of localised knowledge rests on data on codified knowledge (patents), the short distance for which we find significant impacts of localised knowledge on innovation persistence may be related to a generally more confined action space of service innovators when it comes to absorb external knowledge in the innovation process. As service firms are more dependent upon personal interaction in order to absorb external knowledge, geographical distance is likely to play a more prominent role than in manufacturing.

Finally, our research also helps to better understand the drivers and mechanism of innovation persistence in general. This is important, because innovation persistence tends to contribute to productivity and long-term competitiveness of firms (see Lööf and Johansson 2013 for productivity growth; Bianchini and Pellegrino 2017 for employment growth).[12] Our research suggests that creating areas of dense and diversified knowledge is a useful way for strengthening innovation and achieving productivity gains.

Our research is of course subject to several limitations that call for future research efforts. First, our measure of innovation persistence is a simple dichotomous indicator. While engaging in innovation or not is certainly a key decision by firms, persistence of innovation may also refer to the ability to maintain a certain level of commitment over time. Continuous measures on innovation activity, e.g. the amount of innovation expenditures, the number of employees working on innovation projects or the number of ongoing projects may be useful measures in this respect.

Secondly, we rely on only one indicator for external knowledge (patents). There are certainly more knowledge sources relevant to innovation that are only poorly captured by patents. Extending the measurement of the knowledge pool to include non-technological knowledge (e.g. customer requirements, organisational or operational knowledge, experience-based know-how) can provide more insights on whether different types of knowledge show different impacts on innovation persistence at different geographic scales.

Thirdly, our results refer to Germany and its specific geographic structure that differs from other countries. Thus, similar studies in countries with a significantly different regional structure could be useful in order to evaluate whether our findings hold for other geographic settings.

Notes

1. See the explanation on the sources of persistence given in the introduction.
2. In the empirical literature, innovation has been either measured as an input variable (e.g. expenditure for innovation) or as an output variable (e.g. introduction of an innovation; see Antonelli, Crespi, and Scellato 2013; Le Bas and Scellato 2014; Peters 2009; Roper and Hewitt-Dundas 2008). In this paper, we consider input decisions of firms, i.e., the allocation of financial resources to innovation.
3. Overall, a similar picture is observed if we use a wider distance threshold (i.e. 20 kilometres).
4. Again, overall a very similar pattern is observed if we use a wider distance threshold (i.e. 20 kilometres) or if we compare the top quartile to the rest of locations.
5. Specifying the individual heterogeneity as fixed effect (FE) would generally be preferable because FE makes no assumptions about the (conditional or unconditional) distribution or the relation to the initial observation and other observables. However, due to the non-linearity, there is no transformation known that can eliminate fixed effects in panel probit models. Thus, we cannot consistently estimate a FE probit model. While a FE logit model could in principle be estimated using a conditional ML approach, it has the drawback that the identification is based only on the small subsample of firms that switch their innovation status.
6. When taking the means, we leave out the corresponding values of the initial observation period x_{i0} in order to avoid inconsistent estimates (see Wooldridge 2005; Rabe-Hesketh and Skrondal 2013).
7. Ganter and Hecker (2013) use a similar approach to analyse the moderating impact of some firm-level characteristics and include interaction effects between those characteristics and the lagged innovation status.
8. Nomenclature des unités territoriales statistiques, the EU's regional classification system for statistical purposes.
9. The decrease in predicted innovation probabilities with an increasing knowledge pool for past non-innovators is only observed for small distances (within 10 kilometres) in manufacturing.
10. Since we observe no direct significant effect of the local patenting environment, our results suggest a pure moderating effect of the local patenting environment in manufacturing.
11. Larger thresholds are not very meaningful in the context of Germany as the country is not that large in geographic terms. For example, for the geographic centre of the country, a 350km radius would cover the entire territory. A 250km radius from each firm would on average cover more than half of the territory of Germany.
12. Though in a recent paper, Guarascio and Tamagni (2019) could not find that persistent innovators in Spanish manufacturing experience a sales growth premium.
13. Postal areas are fine-grade geographical units. There are about 11,300 units. The average geographical size is 32 square kilometres, with an average diameter of about 6 kilometres, though the size of postal areas is much smaller in urban areas where most of the firms in our sample are located. For large firms, postal codes represent the actual address as these firms have their own postal codes.
14. Since our data cover all patent applications for several decades, we were also able to construct a patent stock measure for each geographical unit. In this case we summed up the patent application filed over the last 20 years. Unreported estimations using this patent stock measure instead of the patent flow measure show qualitatively highly similar results. These are available upon request.
15. Nace (nomenclature statistique des activités économiques dans la communauté européenne) is the official statistical classification of economic activities used in the European Union and is derived from the UN International Standard Industrial Classification (ISIC).
16. This choice is based on previous related studies and is, for example, similar to Baldwin et al. (2008) or Cainelli and Ganau (2018). It is aimed to cover the boundaries of the most pertinent knowledge flows. We have also tested distance bands beyond 50 kilometres but found no significant effects.

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Appendix

Description of our knowledge pool measure

To proxy local knowledge spillovers for innovation persistence, we use patent data. First, we assign each patent (*pat*) *p* to narrowly defined geographical units *l*, using the 5-digit ZIP code ('postal area') of the applicant's address.[13] Secondly, we establish the fields of technology for which a patent is relevant. For this purpose, we consider that patents are not only relevant to the field of technology *m* a patent is belonging to according to its patent class (based on its IPC code) but also for other fields (Jaffe and Trajtenberg 1999). Using patent citation data, we establish a matrix of fields of technology *k* that cite patents from fields of technology *m* (cit_{mk}). This allows us to assign a patent to technologies for which it is potentially relevant and identify the strength of these links. Finally, we link patents to firms using a concordance between 4-digit industry *j* and fields of technology *k* (con_{kj}). For each firm *i* and year *t*, we then calculate the knowledge pool *KnowPool* in a firm's vicinity, using different distance thresholds *r* (5–50 kilometres) and excluding the firm's own patents. *KnowPool* is measured as the (lagged) patent flow (newly applied patents three years prior to year *t*).[14]

The procedure can be summarised as follows:

$$pat_t^{lk} = \sum_{p \in l} pat_{pt}^{lm} cit_{mk} \quad \text{for all } l \in \{1, \ldots, L\} \text{ and } k \in \{1, \ldots, K\} \tag{A.1}$$

$$pat_t^{lj} = \sum_{k=1}^{K} pat_t^{lk} con_{kj} \quad \text{for all } l \in \{1, \ldots, L\} \text{ and } j \in \{1, \ldots, J\} \tag{A.2}$$

$$KnowPool_{it}^{r} = \sum_{l} \sum_{j} pat_t^{lj} \lambda_{ij} \, \omega_{lr_i} - pat_{it} \tag{A.3}$$

with λ_{ij} being an indicator variable that is 1 if firm *i* belongs to industry *j*, and ω_{lr_i} indicating whether postal area *l* is within the distance threshold *r* of firm *i*.

In the following, we explain in more detail how we implement this procedure. Patent data is taken from the Patstat database of the European Patent Office (EPO). We consider all patent applications at the German Patent and Trademark Office (DPMA) as well as applications at the EPO and through the Patent Cooperation Treaty (PCT) procedure at the World Intellectual Patent Office (WIPO) as long as Germany is among the priority countries of these international

[13]Postal areas are fine-grade geographical units. There are about 11,300 units. The average geographical size is 32 square kilometres, with an average diameter of about 6 kilometres, though the size of postal areas is much smaller in urban areas where most of the firms in our sample are located. For large firms, postal codes represent the actual address as these firms have their own postal codes.

[14]Since our data cover all patent applications for several decades, we were also able to construct a patent stock measure for each geographical unit. In this case we summed up the patent application filed over the last 20 years. Unreported estimations using this patent stock measure instead of the patent flow measure show qualitatively highly similar results. These are available upon request.

applications. In case several patent applications represent the same invention, they are counted as one patent only (patent family approach). We consider both patent applications by firms and by others (e.g. private individuals, universities, government research labs) in a year *t*. Each patent is assigned to a geographical unit *l* by the postal code of the applicant. In case a patent has multiple applicants from different postal areas, fractional counting is applied.

To derive relevance-adjusted patent data, we assign every patent to technology patent classes, using the WIPO classification developed by Schmoch (2008). This classification links IPC codes to 35 technology fields. Since patents can have more than one IPC code, they may be assigned to more than one technology field (using fractional counting). We then calculate for each technology field a vector of technology fields that cite this field of technology (cit_{mk}), using data on backward citations in Patstat. For this exercise we consider all patent applications at the DPMA plus EPO and PCT applications with Germany as priority country for the period 1990–2015.

In order to link patent data to a firm's innovation activities, other studies often use a technology proximity measure (e.g. Jaffe 1986) which correlates the technology vector of patents in the region with the technology vector of the firm derived from the firm's own patents. This procedure requires that all firms in the sample have applied for at least one patent. This is not the case, however, if one examines a representative sample of firms across all industries as we do. In our sample, only 13.4% of the firms have at least one patent application. As an alternative approach, we establish a vector of technology fields for each industrial sector using 4-digit Nace rev. 2 codes.[15] For this purpose, we use a matching effort performed at ZEW that linked each patent applicant from Germany to a comprehensive firm-level panel data base, the Mannheim Enterprise Panel (MUP), including more than 3.3 million active German firms as well as information on closed firms and hence allows us to link patent application data and firm data back to the 1990s and earlier (see Bersch et al. 2014 for details on the MUP). For each firm in the MUP, information on its Nace code is available which can be used to calculate a matrix of Nace code times fields of technology (con_{kj}) (see Kortum and Putnam 1997; Dorner and Harhoff 2018 for similar approaches).

Using a geographic information system, we finally calculate the count of our patent measure within discrete distance thresholds of 5, 10, 20, 30, and 50 kilometres.[16] Distances are based on the geographic centres of the postal code area. Thus, we do not have to specify a priori the relevant geographic extension of the knowledge spillovers that influence innovation persistence.

Table A.1. Distribution of firms by industry (in percent).

Sector	Original sample	Estimation sample
Food	4.65	4.51
Textile	3.03	3.18
Wood, paper, printing	6.07	6.17
Chemicals	4.28	4.34
Rubber, plastics	3.21	3.37
Glass, ceramics	2.34	2.42
Metals	7.63	8.36
Machinery	6.96	7.30
Electronics	5.29	5.77
Instruments	4.65	5.00
Vehicles	3.28	3.29
Misc. manufacturing	2.85	2.01
Wholesale	4.15	4.07
Retail	1.69	1.72
Transport, post	7.81	7.25
Banks, insurance	4.69	4.05
Computer, telecom.	5.17	4.89
Technical services	6.22	6.49
Business rel. services	5.10	4.70
Other services	8.08	8.32
Renting	1.28	1.39
Media	1.57	1.40
Total no of observations	90,390	45,858

[15]Nace (nomenclature statistique des activités économiques dans la communauté européenne) is the official statistical classification of economic activities used in the European Union and is derived from the UN International Standard Industrial Classification (ISIC).

[16]This choice is based on previous related studies and is, for example, similar to Baldwin et al. (2008) or Cainelli and Ganau (2018). It is aimed to cover the boundaries of the most pertinent knowledge flows. We have also tested distance bands beyond 50 kilometres but found no significant effects.

Table A.2. Distribution of firms by firm size (in percent).

No. of employees	Original sample	Estimation sample Total	Manuf.	Services
0–49	54.78	55.63	47.93	65.33
50–99	11.63	12.24	13.49	10.67
100–249	11.49	12.05	14.76	8.65
250–999	10.51	10.10	12.27	7.36
1000–9999	10.03	8.49	10.03	6.56
10,000 and more	1.58	1.48	1.52	1.43
Total no of observations	89,485	45,858	25,556	20,302

Note: In the original sample, 905 out of 90,390 observations have missing information on employment.

Table A.3. Innovation behaviour.

Innovation indicator	Original sample	Estimation sample Total	Manuf.	Services
% with innovation expenditure >0	53.33	52.71	62.97	39.80
% with product innovation	44.82	41.97	52.48	28.73
% with process innovation	36.94	35.26	41.44	27.49

Table A.4. Robustness analysis I: large distance effects.

	Manufacturing		Services	
	(1) Up to 100 km	(2) Up to 250 km	(3) Up to 100km	(4) Up to 250 km
Inno$_{t-1}$	0.452***	0.452***	0.486***	0.486***
	(0.017)	(0.017)	(0.015)	(0.015)
KnowlPool	0.003	0.003	0.001	0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Inno$_{t-1}$**KnowlPool*	0.000	−0.001	0.001	0.000
	(0.004)	(0.004)	(0.005)	(0.004)
Firm-level controls	Y	Y	Y	Y
Regional controls (NUTS3)	Y	Y	Y	Y
Region fixed effects (NUTS2)	Y	Y	Y	Y
Sector fixed effects (Nace2)	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
σ_v	0.619	0.619	0.521	0.521
	(0.030)	(0.030)	(0.030)	(0.030)
ρ	0.277	0.277	0.213	0.214
	(0.019)	(0.019)	(0.019)	(0.019)
Observations	25,556	25,556	20,302	20,302
Groups	8433	8433	7275	7275
Log likelihood	−8403	−8404	−8082	−8082

Notes: Marginal effects of a correlated random effects model. Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year $t-3$ (patent flow approach) within the different distance thresholds. Clustered standard errors in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% levels. For the set of firm-level and regional control variables see Table 2.

Table A.5. Robustness analysis II: longer persistence lags.

	Manufacturing					Services				
	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20 km	(4) Up to 30 km	(5) Up to 50 km	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20 km	(4) Up to 30 km	(5) Up to 50 km
Model A: Two-year lag										
Inno$_{t-2}$	0.255***	0.242***	0.236***	0.228***	0.207***	0.317***	0.290***	0.267***	0.257***	0.244***
	(0.029)	(0.026)	(0.024)	(0.022)	(0.020)	(0.031)	(0.027)	(0.024)	(0.022)	(0.020)
KnowlPool	−0.002	−0.007*	−0.000	0.003	0.008*	0.009**	0.005	0.001	−0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Inno$_{t-2}$**KnowlPool*	0.010***	0.010**	0.012***	0.013**	0.006	0.015***	0.012***	0.010*	0.009	0.004
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)

(*Continued*)

Table A.5. Continued.

	Manufacturing					Services				
	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20 km	(4) Up to 30 km	(5) Up to 50 km	(1) Up to 5 km	(2) Up to 10 km	(3) Up to 20 km	(4) Up to 30 km	(5) Up to 50 km
Observations	16,430	16,430	16,430	16,430	16,430	12,810	12,810	12,810	12,810	12,810
Groups	5236	5236	5236	5236	5236	4384	4384	4384	4384	4384
Model B: Three-year lag										
$Inno_{t-3}$	0.180***	0.189***	0.177***	0.162***	0.140***	0.239***	0.215***	0.186***	0.169***	0.157***
	(0.033)	(0.031)	(0.028)	(0.025)	(0.023)	(0.036)	(0.031)	(0.028)	(0.026)	(0.024)
KnowlPool	0.002	−0.005	−0.000	0.001	0.003	0.013***	0.008*	0.003	0.004	0.008
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
$Inno_{t-3}$*KnowlPool*	0.009**	0.014***	0.015***	0.014**	0.008	0.015***	0.013***	0.010*	0.006	−0.000
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	13,340	13,340	13,340	13,340	13,340	10,255	10,255	10,255	10,255	10,255
Groups	4315	4315	4315	4315	4315	3662	3662	3662	3662	3662

Notes: Marginal effects of a correlated random effects model. Model A and B use a two-year lag and two-year lag of the innovation variable, respectively, to capture persistence in innovation activities. Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year $t-3$ (patent flow approach) within the different distance thresholds. Included in each model but not reported is the set of firm-level and regional control variables and the region, sector and year fixed effects as in the main results Tables 2 and 3. Clustered standard errors in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% levels.