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DISCUSSION PAPER

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Local Knowledge Spillovers and Innovation Persistence of Firms

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Local Knowledge Spillovers and Innovation Persistence of Firms*

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Abstract: Recent empirical evidence has shown that firm's innovation behavior exhibits high persistency but not much is known about potential contingencies affecting the degree of persistence. This paper focuses on the role of the local knowledge environment and asks how local knowledge spillovers affect firms' innovation persistence. The empirical analysis draws upon a representative panel data set of firms in Germany from 2002-2016, complemented by detailed geographic information of patent activity over discrete distances to proxy local knowledge spillovers. Based on correlated random effects probit models that control for state dependence, unobserved individual heterogeneity and endogenous initial conditions, our results corroborate former evidence that persistency in innovation is driven by true state dependence. More importantly, we find that the local patenting activity positively moderates firms´ degree of persistency in innovation behavior. This is a novel firm-level mechanism that can explain the widening of spatial disparities in innovation performance. Estimations with different distance bands show that the strength of knowledge spillovers that contribute to innovation persistence via true state dependence declines rather rapidly with increasing distance.

Keywords: Innovation, persistence, location, knowledge spillovers

JEL: O31, R1, D22

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1. Introduction

Innovation is a one of the main sources of economic growth. As successful innovation requires continuous commitment, the persistency of firms' innovation activities has attracted increasing attention. As a result, there exists now a quite established literature on innovation persistence at the micro level both empirically as well as from a theoretical perspective (see, for example, Cefis and Orsenigo, 2001; Peters, 2009; Martínez-Ros and Labeaga, 2009; Raymond et al., 2010 amongst others). This literature demonstrates that firms exhibit strong persistency in their innovation behavior.

Persistence in innovation can result from true state dependence (Heckman, 1981) when there is a causal relationship with the decision to innovate in one period increasing the propensity to innovate also 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 by doing” (Geroski et al., 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 those characteristics are usually highly persistent over time, this will also lead to observed persistence in innovation behavior, and thus spurious state dependence may be identified (Peters, 2009). It is hence important to control for such observable and unobservable firm characteristics. The literature has found compelling evidence for true state dependence and has also analyzed several firm internal drivers of persistence.

However, little attention has been paid to the role of locational factors, and local knowledge spillovers in particular. 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-by-doing by providing easy and cheap access to complementary resources required for a firm's innovation activity. All this could increase innovation persistence. This paper is among the first to provide evidence for the causal effect of local knowledge spillovers on persistence that derives from true state dependence of innovation activities, i.e. we focus on how the local knowledge environment moderates true state dependence. We employ a representative, comprehensive panel data set of firms in Germany, covering a 15-year period and estimate correlated random effects probit models. The model accounts for state dependence, unobserved heterogeneity and initial conditions and allows unobserved factors to be correlated with the observables. This is important because unobserved factors could be correlated with firms' initial location decision. For example, firms with unobserved characteristics that are positively linked to innovate may be attracted to regions that offer better conditions for innovating.

The estimation results show that the local patenting activity significantly moderates firms´ persistence in innovation activities. Estimations with different distance bands furthermore show that the role of knowledge spillovers for innovation persistence declines with increasing distance. These patterns are observed for both manufacturing and service firms. However, in services, the knowledge spillovers that contribute to innovation persistence are spatially more constrained than in manufacturing.

Our research contributes to the debate about innovation persistence in several ways. First, we contribute towards the literature on innovation dynamics and the drivers and mechanism of innovation persistence by showing that true state dependence is actually moderated by firms' external knowledge environment. Previous research in this field has almost exclusively focused on intra-firm drivers of persistence. Second, the findings in this paper also contributes to the literature on knowledge spillovers by showing that spillovers affect innovation persistence. Furthermore, we use a geographic information system (GIS) to calculate patents over discrete distances based on postal code information to proxy knowledge spillovers. Previous research on knowledge spillovers has mostly relied on larger administrative regions. Far less is still known about the role of knowledge at finer scales of geographical resolution. To the best of our knowledge, this is the first empirical analysis that examines the role of local knowledge spillovers for innovation persistence using a micro-geographic distance-based approach. Finally, our research is also of interest to the literature on regional heterogeneity in innovation performance. We show that firms in areas with higher patenting activity – i.e. knowledge-rich areas – show greater persistence. This is a firm-level mechanism that can explain the growing concentration of innovation and the widening of spatial disparities in innovation performance that has recently be observed (Castellani, 2017; Rammer and Schubert, 2018; Kerr and Robert-Nicoud, 2019). Our results are also relevant to regional policy. Since stopping innovation activities may harm firm's long-term competitiveness, low innovation persistence may further widen reginal economic disparities. Recent research has also shown that innovation contributes to the resilience of regions to economic shocks (Bristow and Healy, 2018). It is therefore important to gain a better understanding of the factors that contribute to innovation persistence not only from the firm's perspective but also for designing policies.

The remainder of this paper is organized 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 and are presented in Section 5. Section 6 offers conclusions.

2. Local Knowledge Spillovers and Innovation Persistence

In analyzing the 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 huge 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 Feldmann, 2004; Carlino and Kerr, 2015; Audretsch and Feldman, 1996; Feldman and Audretsch, 1999; Simmie, 2002; Thompson, 2006). There are few works, however, that have combined the two strands and have looked at the role of local knowledge spillovers for the persistence of a firm's innovation activity (Tavassoli and Karlsson, 2018, is a recent exception). In this paper, we bring together these two strands.

Theoretical explanations of innovation persistence stress four main mechanisms that keep firms in or out of innovation activities. 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) as well as hiring specialized staff for performing innovation activities which 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). Secondly, successful innovation generates extra profits that can be used to finance new innovation activities ('success breeds success'; Flaig and Stadler, 1994). As innovative firms on average are more successful than non-innovative ones (Geroski et al., 1993; Leiponen, 2000; Cefis and Ciccarelli, 2005; Love et al., 2009), past innovation provides the financial basis for future innovation. Thirdly, innovation activities are subject to "learning-by-doing". Firms learn by innovating, and the knowledge they acquire from past innovation can contribute to new innovation (Geroski et al., 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.

A factor that has received little attention in research on innovation persistency so far is a firm's local knowledge environment. We argue that the availability or absence of local knowledge spillovers changes the way the four aforementioned mechanisms work. Local knowledge spillovers may hence be regarded as a moderator that strengthens or softens the factors leading to innovation persistence. In the following, we discuss the likely impacts of a firm's local knowledge environment for the four main mechanisms that lead to innovation persistency.

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 by external ones, e.g. by outsourcing of 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 will rather 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 et al., 2017). One may expect firms in a thick knowledge environment to 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 successfully innovate 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 for 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-relevant knowledge in a region decreases fixed and sunk costs of innovation and hence reduces barriers to entry or exit innovation activities.

A critical issue when analyzing 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 quite different results. Wallsten (2001) studied participation in the Small

Business Innovation Research program in the U.S. and found that firms are more likely to receive a grant if their neighbors within a 1/10 of a mile received a grant. The effect rapidly diminishes with increasing distance and disappears by 5 miles. Rammer et al. (2019) found that the impact of local public knowledge sources (universities, research institutes) on firms' innovation in an urban environment diminishes already after some 100 meters. These results suggest highly localized knowledge spillovers at small geographical scales (see also Rosenthal and Strange, 2003; Murata et al. 2014). 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) analyzed 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 23km distance.

At the same time, the literature on the geography of knowledge flows stresses the importance of inter-regional and international knowledge (Bathelt et al. 2004; Gertler and Levitte, 2005). Niosi and Yhegu (2005) argue in the case of aerospace clusters that knowledge spillovers are much less spatially constrained. Bottazzi and Peri (2003) analyzed the impact of R&D spending on the output of new ideas in European Regions and found spillovers that extend within a distance of 300km. Nevertheless, as Bathelt et al. (2004) argue, 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).

Regarding spatial differences in innovation persistence, the study by Cefis and Orsenigo (2001) highlights that the level of innovation persistence is country-specific which could be due to different institutional set ups, different technological specialization and different costs for conducting innovation activities in place. Filippetti and Archibugi (2011) also highlight country differences in the degree to which firms have decreased their innovation expenditure in response to the 2008 economic crisis. They point towards differences in the National Systems of Innovation as factors shaping the innovation behavior of firms in response to the crisis. We argue that beyond country differences there can also be important local and regional heterogeneity in innovation persistence within countries given the role of localized knowledge and knowledge spillovers.

There is some recent empirical evidence that points in this direction. Holl and Rama (2016) found, for example, 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 investigate firms' probability of abandoning in-house R&D in Spain since the onset of the economic crisis and also show significant regional heterogeneity. Using a sample of Italian manufacturing firms, Antonelli et al. (2013) find a significant role of the reginal context for TFP persistence. They argue that this reflects innovation persistence.

The most closely related paper to our research is Tavassoli and Karlsson (2018). They use data of 574 firms from 5 waves of the Community Innovation Survey in Sweden between 2002 and 2012. They apply a dynamic random effects probit model to analyze various regional characteristics and how they affect persistency in the introduction of product, process, organizational and marketing innovation. In order to analyze regional differences, they split the sample of firms in three categories based on tercile values for total regional employment size, regional employment in knowledge-intensive service sectors, and total number of innovative firms in the functional region. Their results show that firms in regions with thicker labour markets, with more knowledge-intensive service providers, and with a greater number of innovative firms tend to show a higher probability of being persistent innovators. This suggests that the regional context can indeed affect innovation persistence at the firm level. Nevertheless, their findings regarding the role of location for innovation persistence are not completely conclusive as in some cases persistence is nearly of the same magnitude in the lowest tercile.

How the local environment of a firm moderates its innovation persistence has not yet been sufficiently explored. Particularly, to date there is yet no consistent evidence on the role of local knowledge spillovers on innovation persistence. In this paper, we use micro-geographic data and adopt a distance-based approach to unveil processes that would otherwise be hidden at larger levels of spatial aggregation. If the relevant knowledge spillovers operate at fine spatial scales, studies based on relatively large fixed geographic areas or administrative boundaries are likely to underestimate the role of knowledge spillovers. Moreover, we implement an empirical strategy aimed at providing evidence on the causal effect of the local knowledge environment on persistence in innovation activities.

3. Data and Descriptive Results

We use data from the Mannheim Innovation Panel (MIP) which provides information regarding the innovation behavior 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). 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. However, since participation in the MIP survey is voluntary, many firms did not necessarily respond in consecutive years; a requirement for the empirical analysis. Moreover, not all firms always respond to all questions. Thus, we end up with an unbalanced panel of nearly 15,266 different firms (8,373 manufacturing firms and 7,213 service sector firms, among them 320 firms switching industries over the time period) and 66,479 observations for our empirical analysis. The average number of consecutive observations per firm of is 4.4 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 45,898 observations. 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 behavior. Overall, our estimation sample reflects the original sample characteristics quite well and does not raise any obvious selectivity concerns.

Following Peters (2009), this paper focuses on innovation input. The dependent variable innovation, $Inno_{it}$, equals 1 if firm i is engaged in innovation activities in year t, measured here as having positive innovation expenditure in year t. The MIP and CIS also collect output-related information, specifically the introduction of new products and processes. However, these variables refer to a three-year period and thus cause overlapping 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. Other papers that have focused on input rather than innovation output variables are, for example, Máñez et al. (2009) and Arqué-Castells (2013). As argued in Arqué-Castells (2013) input variables reflect innovation effort rather than only the success in innovation and policies are usually geared towards the input side of the innovation process.

To examine the importance of local knowledge spillovers for innovation persistence, we use patent data. 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 us to both locate knowledge sources and to assess the relevance of this knowledge for each firm. We derive our knowledge spillover measure through a three-stage procedure. 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. Secondly, we establish the fields of technology for which a patent is relevant. For this purpose, we consider that patents are not only relevant for 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 to 50 kilometers) and excluding the firm's own patents. $KnowPool$ is measured as the (lagged) patent flow (newly applied patents three years prior to year t). For robustness checks, we also calculate a patent stock variable.

The procedure can be summarized as follows:

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

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

$$KnowPool_{it}^{r} = \sum_l \sum_j pat_t^{lj}\, \lambda_{ij}\, \omega_{lr_i} - pat_{it} \tag{3}$$

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 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 to 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[1]. 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., 2004 for details on the MUP). For each firm in the MUP,

[1] 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).

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 5km, 10km, 20km, 30km, and 50km. Distances are based on the geographic centers 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 1 shows the transition probabilities for the dependent variable $Inno$. We compare firms located 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 5km 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 5km distance threshold, we observe that in areas with a patenting activity in the upper quartile, about 86% 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 also 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.[2] This suggests that there is indeed a positive link between the local knowledge environment and innovation persistence.

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[2] Overall, a similar picture is observed if we use a wider distance threshold (i.e. 20km).

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

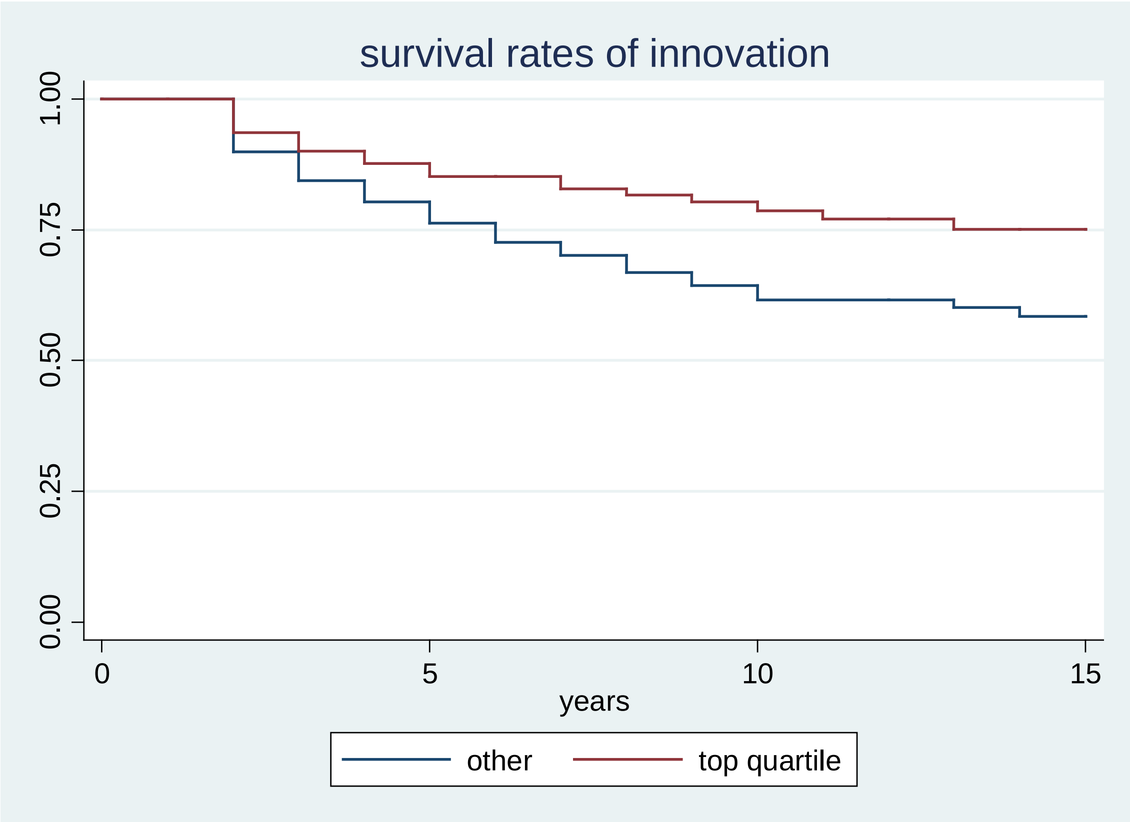
		All sample firms		Manufacturing		Services	
Local patenting activity		NON-INNO	INNO	NON-INNO	INNO	NON-INNO	INNO
Lowest quartile	NON-INNO	89.2	10.8	87.2	12.8	90.5	9.5
	INNO	24.7	75.3	17.1	82.9	39.0	61.0
Highest quartile	NON-INNO	85.9	14.1	85.6	14.4	86.2	13.8
	INNO	13.6	86.4	9.5	90.5	21.8	78.2

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 firms located in the upper quartile versus the rest of the firms for the distance threshold of 5km.[3] Firms in areas with a high patenting activity again demonstrate higher survival rates in innovation. The difference between the survivor functions is significant at the 1% level (p-value 0.0015) as indicated by the log-rank test.

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. Observed and unobserved firm characteristics have to be accounted for in an econometric approach in order to identify causal effects.

[3]Again, overall a very similar pattern is observed if we use a wider distance threshold (i.e. 20km) or if we compare the top quartile to the bottom quartile.

Figure 1. Survival rates of innovation (%) in firms being in top patenting quartile locations compared to firms in the rest of locations



Notes: The graph shows Kaplan-Meier survival estimates of innovation behavior in firms differentiated by the size of the local knowledge pool. Top quartile defines locations above the 75th percentile of patent activity within a distance of 5km.

4. Econometric Model and Estimation Approach

Our empirical model is based on a simple model of optimization for a firm facing the decision to invest in innovation. A profit maximizing firm makes its decision based on expected profits (benefits minus costs) from innovation, now and in the future. It engages in innovation if the expected present value of profits from investment in innovation $Inno_{it}^{*}$ is positive. $Inno_{it}^{*}$ depends on past realized 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 costs of innovation or on the hand past innovation increases the expected benefits of future innovation due to success breeds success, learning effects or innovation-supportive market structures. These arguments can imply that the probability of engaging in innovation in the current period will depend on the decision to innovate in past periods. 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:

$$Inno_{it}^{*} = \theta Inno_{it-1} + \beta x_{it} + \varphi_i + \varepsilon_{it} \tag{4}$$

ε_{it} captures time variant idiosyncratic error shocks. It is assumed that the conditional distribution of ε_{it} is i.i.d. $N(0,1)$. Unfortunately, we don't observe the expected present value of profits from investing in innovation, but instead observe whether or not the firm is engaged in innovation activities or not. We assume that the firm engages in innovation if the expected net present value of profits is positive. Consequently, the innovation status of the firm i in period t can be denoted by the binary indicator $Inno_{it}$

$$Inno_{it} = \begin{cases} 1 & if\ Inno_{it}^{*} > 0 \\ 0 & otherwise \end{cases} \tag{5}$$

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

$$Pr(Inno_{it} = 1 | x_{it}, Inno_{it-1}, \varphi_i) = F(\theta Inno_{it-1} + \beta x_{it} + \varphi_i) \tag{6}$$

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 so called "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. Following Wooldridge (2005), we thus model the unobserved heterogeneity conditional on the initial condition, $Inno_{i0}$, and the time averages of the exogenous variables.

$$\varphi_i = \partial_0 + \partial_1 Inno_{i0} + \partial_1 \bar{x}_i + \vartheta_i \tag{7}$$

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

The key questions of our paper is how the local knowledge environment moderates firms' innovation persistence. For this purpose, we include the knowledge pool that is relevant for firm i at time t located in region l, $KnowPool_{it}^{l}$, and its interaction term with the lagged innovation status $Inno_{it-1}$.[4] 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 (5, 10, 20, 30, 50 km) as described in the previous section. The augmented latent model is then given by

$$Inno_{it}^{*} = \beta x_{it} + \theta Inno_{it-1} + a_1 KnowPool_{it}^{l} + \alpha_2\left(Inno_{it-1} * KnowPool_{it}^{l}\right) + \partial_0 + \partial_1 Inno_{i0} + \partial_1 \bar{x}_i + \vartheta_i + \varepsilon_{it} \quad (8)$$

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 to innovate may be attracted to regions that offer better conditions for innovating.

Firm level control variables: In line with previous theoretical and empirical studies on innovation (e.g. Schumpeter, 1942; Cohen and Klepper, 1996), we control for firm size (measured as the log of the number of employees). Firm size has been found to be an important determinant of whether or not a firms is engaged in innovation activities in many studies on innovation persistence (e.g. Peters, 2009; Raymond et al., 2010; Clausen et al., 2012; Ganter and Hecker, 2013), as a minimum of resources is required to fund innovation activities.

Furthermore, we control for firm age (log of years since the firm was created), export status (1 if firm sells on international markets), and group status (1 if 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 organizational capabilities, larger

[4] Ganter and Hecker (2013) use a similar approach to analyze the moderating impact of some firm-level characteristics and include interaction effects between those characteristics and the lagged innovation status.

competitive pressure but also larger benefits from innovation due to larger market size and technology sourcing that make them more likely to innovate (Peters et al. 2018). Firms belonging to a group are more likely to innovate as they may benefit also from within-group knowledge spillovers (Raymond et al., 2010) as well as resources that help to sustain innovation efforts. In our estimations, all these firm-specific control variables are lagged one year to alleviate potential endogeneity issues.

Sectoral and regional controls: Previous research has furthermore shown that persistence varies among different industries. Firms in high-tech industries tend to show higher persistence than firms in low-tech industries (Raymond et al., 2010). Our specification therefore includes 2-digit Nace sector dummies. Finally, we include NUTS[5] level 2 regional dummies to control for unobserved fixed region-specific factors that could influence persistence in innovation.

5. Results

Table 2 shows how the local knowledge environment affects the persistence of innovation. Displayed are marginal effects and standard errors of the correlated random effects probit model (8) for firms in manufacturing. 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 and the potential self-selection of firms into areas of higher patenting activity. Across different specifications, we estimate this difference to be between 47 to 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 to 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.

[5] Nomenclature des unités territoriales statistiques, the EU's regional classification system for statistical purposes.

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

	(1) Up to 5 km	(2) Up to 10km	(3) Up to 20km	(4) Up to 30km	(5) Up to 50km
$Inno_{t-1}$	0.525*** (0.020)	0.509*** (0.018)	0.494*** (0.016)	0.485*** (0.015)	0.477*** (0.014)
KnowlPool	-0.002 (0.003)	-0.000 (0.003)	0.000 (0.003)	0.003 (0.003)	0.003 (0.003)
$Inno_{t-1}$*KnowlPool	0.011*** (0.003)	0.011*** (0.003)	0.009** (0.003)	0.008** (0.004)	0.007 (0.004)
Size	0.024 (0.023)	0.024 (0.023)	0.024 (0.023)	0.024 (0.023)	0.024 (0.023)
Age	-0.011* (0.006)	-0.011* (0.006)	-0.012* (0.006)	-0.012* (0.006)	-0.012* (0.006)
Group	-0.026 (0.024)	-0.025 (0.024)	-0.026 (0.024)	-0.026 (0.024)	-0.026 (0.024)
Export	0.073*** (0.023)	0.073*** (0.023)	0.074*** (0.023)	0.074*** (0.023)	0.074*** (0.023)
Inno_0	0.290*** (0.014)	0.292*** (0.014)	0.292*** (0.014)	0.292*** (0.014)	0.293*** (0.014)
Mean(Size)	0.044* (0.023)	0.044* (0.023)	0.044* (0.023)	0.044* (0.023)	0.044* (0.023)
Mean(Group)	0.035 (0.028)	0.035 (0.028)	0.036 (0.028)	0.036 (0.028)	0.035 (0.028)
Mean(Export)	0.080*** (0.026)	0.079*** (0.026)	0.079*** (0.026)	0.079*** (0.026)	0.079*** (0.026)
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_{υ}	0.614 (0.029)	0.616 (0.029)	0.616 (0.029)	0.615 (0.029)	0.616 (0.029)
ρ	0.274 (0.019)	0.275 (0.019)	0.275 (0.019)	0.274 (0.019)	0.275 (0.019)
Observations	25567	25567	25567	25567	25567
Groups	8447	8447	8447	8447	8447
Log likelihood	-8405.8	-8406.9	-8409.9	-8409.3	-8411.3

Notes: Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year *t - 3* (patent flow) within the different distance thresholds. Standard errors in parentheses. ***, **, * indicate statistical significance at the 99, 95 and 90% levels.

Our key variables of interest is the interaction term of the local knowledge pool with the lagged innovation status, $Inno_{t-1} \times KnowPool_{it}^{l}$. With the inclusion of this interaction term to measure how the local knowledge environment moderates innovation persistence, the knowledge pool itself does not turn out to be significant. However, the interaction term matters with its size and significance falling in distance. In column (1), the distance threshold is up to 5 kilometers from the postal code centroid of the focal firm. The interaction term is positive and highly statistically significant at the 1% level. The estimated coefficient is 0.011. This positive interaction with the lagged innovation status confirms that persistence is indeed higher for firms in areas with more patenting activity. This provides evidence that the local patenting environment is moderating firms' true state dependence and that local knowledge spillovers contribute to firms' innovation persistence. This is 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. Our results also provide empirical support to the argument put forward in Castellani (2017) that a strong local flow of knowledge can lead to persistence in innovation activities.

In column (2) we widen the distance band up to 10 kilometers. The interaction term continues to be positive and significant, and of the same magnitude. In column (3) we extend the distance threshold up to 20 kilometers. Now the interaction term is slightly smaller with a marginal effect of 0.009 and significance drops to the 5 percent level. Within a 30km radius, the marginal effect reduces to 0.008 and significance at the 5 percent level. Beyond the 30km threshold we observe that the interaction term further falls in magnitude and loses significance. This suggests that the spillovers that contribute to innovation persistence in manufacturing tend to fall by distance and are spatially constrained within 30 kilometers. [6]

Table 3 shows the corresponding results for the service sector. Innovation in services is highly state dependent and of similar magnitude than in manufacturing. For services, the local knowledge pool $KnowPool_{it}^{l}$ is significant up to 30 kilometers indicating a positive influence of the local patenting activity on the probability of engaging in innovation activities. In contrast, the interaction term is only significant up to the 10km distance threshold, indicating that in services too, the local knowledge environment moderates innovation persistence but the effect is spatially more constrained. Beyond 10 kilometers, we do not observe a significant impact of the local patenting environment on innovation persistence. Compared to manufacturing, these results highlight that local knowledge spillovers are even more localized in services.

[6] In unreported estimations we have also tested for further distance bands beyond 50 kilometres but found no significant effects.

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

	(1) Up to 5 km	(2) Up to 10km	(3) Up to 20km	(4) Up to 30km	(5) Up to 50km
$Inno_{t-1}$	0.518*** (0.020)	0.512*** (0.018)	0.489*** (0.016)	0.484*** (0.015)	0.486*** (0.014)
KnowlPool	0.006*** (0.002)	0.006*** (0.003)	0.007*** (0.003)	0.009*** (0.003)	0.005 (0.003)
$Inno_{t-1}$*KnowlPool	0.007** (0.003)	0.007** (0.003)	0.002 (0.003)	0.001 (0.004)	0.003 (0.004)
Size	0.019 (0.020)	0.019 (0.020)	0.020 (0.020)	0.020 (0.020)	0.021 (0.020)
Age	-0.031*** (0.007)	-0.031*** (0.007)	-0.032*** (0.007)	-0.032*** (0.007)	-0.032*** (0.007)
Group	-0.004 (0.025)	-0.004 (0.025)	-0.003 (0.025)	-0.003 (0.025)	-0.003 (0.025)
Export	0.012 (0.024)	0.012 (0.024)	0.012 (0.024)	0.011 (0.024)	0.012 (0.024)
$Inno_0$	0.241*** (0.015)	0.240*** (0.015)	0.243*** (0.015)	0.243*** (0.015)	0.244*** (0.015)
Mean(Size)	0.026 (0.020)	0.026 (0.020)	0.025 (0.020)	0.024 (0.020)	0.024 (0.020)
Mean(Group)	0.052* (0.030)	0.052* (0.030)	0.053* (0.030)	0.053* (0.030)	0.055* (0.030)
Mean(Export)	0.126*** (0.029)	0.128*** (0.028)	0.131*** (0.028)	0.132*** (0.028)	0.134*** (0.028)
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_υ	0.525 (0.029)	0.521 (0.029)	0.522 (0.029)	0.524 (0.029)	0.527 (0.029)
ρ	0.216 (0.019)	0.213 (0.019)	0.214 (0.019)	0.215 (0.019)	0.217 (0.019)
Observations	20331	20331	220331	20331	20331
Groups	7289	7289	7289	7289	7289
Log likelihood	-8092.4	-8093.1	-8100.9	-8099.3	-8104.2

Notes: Knowledge pool is based on the number of firm-specific technology-relevant patent applications in year *t - 3* (patent flow) within the different distance thresholds. Standard errors in parentheses. ***, **, * indicate statistical significance at the 99, 95 and 90% levels.

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 strongly bounded in space.

Robustness checks: Since our data cover all patent applications for several decades, we are able to construct a patent stock measure for each geographical unit. In this case we sum up the patent application filed over the last 20 years. Table A.4 and Table A.5 in the Appendix depicts the estimation results of the correlated random effects probit model for manufacturing and services respectively, using the patent stock instead of patent flows as measure for $KnowPool$. A fairly similar picture emerges with some smaller differences for services. Using patent stock data instead of patent flows results in a spatially somewhat less constrained effect of local knowledge spillovers on innovation persistence of service firms.

In another robustness check we further demonstrate that our results are not driven by very large firms. Excluding very large corporations (more than 10,000 employees), results are again qualitatively the same.

6. Conclusions

This paper analyzed the role of a firm's local knowledge environment for the persistence of innovation activities. We employ a panel data set spanning 15 years for a representative sample of manufacturing and service firms in Germany. The local knowledge pool is measured by firm-specific technology-relevant patents in a firm's vicinity, using different distance thresholds.

Local knowledge not only influences the probability that a firm engages in innovation (which is particularly true for services), but our results most intriguingly show that the local knowledge environment also significantly moderates innovation persistence. This is a different mechanism through which local knowledge influences innovation activity.

Our results show higher innovation persistency for firms with a rich knowledge base (relevant to the firm's activities) in their direct neighborhood. This adds an explanation of why centers 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, 2019 for the U.S.).

The moderating effect is highest for very short distances (up to 10km) and then diminishes very quickly. There has been an ongoing debate in the literature on the geographic scope of knowledge flows (Breschi, 2011). Our findings are consistent with highly localized knowledge flows. Despite the increasing globalization of innovation, our results point to a significant and spatially very constrained role of the local knowledge context for innovation persistence. The effect of knowledge spillovers on innovation persistence is spatially more constrained in services than in manufacturing. Our research contributes to a better understanding on the drivers and mechanism of innovation persistence. This is important, because innovation persistence contributes to the long-term competitiveness of firms (see

Lööf and Johannson, 2013 for productivity growth; Bianchini and Pellegrino, 2017 for employment growth).[7]

This paper also helps to advance our understanding of spatial and regional heterogeneity in innovation performance. Innovations are not only important from the point of view of the individual firm, but also for the competitiveness of regional and national economies. Innovation persistence is thus a pertinent issue for public policy (Hecker and Ganter, 2014). On the one hand, our results suggest that regional innovation leadership can become self-sustaining. The fact that innovation persistency is enhanced by a thick knowledge environment suggests furthermore that policies that manage to raise the local innovation performance can have long lasting effects. On the other hand, our results also put emphasis on local preconditions and that they can constrain any policy efforts. Lagging areas that lack a sufficient knowledge base for successful policy implementations may fall even further behind. Recent empirical evidence (Castellani, 2017; Rammer and Schubert, 2018; Kerr and Robert-Nicoud, 2019) shows that over the last decades regions with already higher patenting activity have indeed increased their rate of innovation and left behind other regions. Our research has identified a firm-level mechanism that can explain such a widening of spatial disparities in innovation performance.

[7] Though in a recent paper Guarascio and Tamagni (2019) could not find that persistent innovators in Spanish manufacturing experience a sales growth premium.

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Appendix

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	6.16
Chemicals	4.28	4.34
Rubber, plastics	3.21	3.37
Glass, ceramics	2.34	2.42
Metals	7.63	8.35
Machinery	6.96	7.29
Electronics	5.29	5.78
Instruments	4.65	5.00
Vehicles	3.28	3.30
Misc. manufacturing	2.85	2.01
Wholesale	4.15	4.06
Retail	1.69	1.71
Transport, post	7.81	7.24
Banks, insurance	4.69	4.06
Computer, telecom.	5.17	4.90
Technical services	6.22	6.51
Business rel. services	5.10	4.71
Other services	8.08	8.31
Renting	1.28	1.39
Media	1.57	1.40
Total no of observations	90,390	45,898

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

No. of employees	Original sample	Estimation sample
0-49	54.78	55.32
50-99	11.63	12.25
100-249	11.49	12.17
250-999	10.51	10.22
1000 - 9999	10.03	8.59
10000 and more	1.58	1.45
Total no of observations	89,485	45,898

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

Table A.3: Innovation behavior

Innovation indicator	Original sample	Estimation sample
% with positive innovation expenditure	53.33	52.71
% with product innovation	44.82	41.95
% with process innovation	36.94	35.21

Table A.4. Manufacturing: Marginal effects of correlated random effects probit estimations: Knowledge pool based on the firm-specific technology-relevant patent stock in year $t-3$ within different distance thresholds

	(1)	(2)	(3)	(4)	(5)
	Up to 5 km	Up to 10km	Up to 20km	Up to 30km	Up to 50km
$Inno_{t-1}$	0.487***	0.478***	0.466***	0.461***	0.462***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)
KnowlPool	-0.002	-0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$Inno_{t-1}$*KnowlPool	0.007***	0.009***	0.007**	0.006*	0.003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Size	0.024	0.024	0.024	0.024	0.024
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Age	-0.011*	-0.011*	-0.011*	-0.011*	-0.012*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Group	-0.026	-0.026	-0.027	-0.026	-0.026
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Export	0.073***	0.074***	0.074***	0.074***	0.074***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$Inno_0$	0.292***	0.292***	0.292***	0.292***	0.294***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mean(Size)	0.044*	0.045*	0.044*	0.045*	0.045*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Mean(Group)	0.035	0.036	0.036	0.035	0.035
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Mean(Export)	0.080***	0.078***	0.079***	0.079***	0.080***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
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_{υ}	0.615	0.615	0.614	0.614	0.617
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
ρ	0.275	0.275	0.274	0.274	0.276
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	25,567	25,567	25,567	25,567	25,567
Groups	8,447	8,447	8,447	8,447	8,447
Log likelihood	-8409.2	-8409.9	-8410.7	-8413.0	-8415.8

Standard errors in parentheses. ***, **, * indicate statistical significance at the 99, 95 and 90% levels.

Table A.5. Services: Marginal effects of correlated random effects probit estimations: Knowledge pool based on the firm-specific technology-relevant patent stock in year $t-3$ within different distance thresholds

	(1) Up to 5 km	(2) Up to 10km	(3) Up to 20km	(4) Up to 30km	(5) Up to
$Inno_{t-1}$	0.498***	0.489***	0.479***	0.476***	0.477***
	(0.014)	(0.013)	(0.012)	(0.013)	(0.015)
KnowlPool	0.004*	0.004*	0.001	0.001	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$Inno_{t-1}$*KnowlPool	0.007***	0.006**	0.006*	0.004	0.002
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Size	0.019	0.019	0.020	0.020	0.020
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Age	-0.031***	-0.032***	-0.032***	-0.032***	-0.032***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Group	-0.004	-0.005	-0.005	-0.004	-0.004
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Export	0.012	0.013	0.012	0.012	0.012
	(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)	0.026	0.025	0.024	0.024	0.024
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Mean(Group)	0.053*	0.054*	0.057*	0.057*	0.057*
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Mean(Export)	0.128***	0.128***	0.132***	0.134***	0.134***
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)
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_{υ}	0.525	0.521	0.522	0.524	0.527
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
ρ	0.216	0.213	0.214	0.215	0.217
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	20,331	20,331	20,331	20,331	20,331
Groups	7,289	7,289	7,289	7,289	7,289
Log likelihood	-8094.4	-8097.4	-8104.1	-8106.2	-8106.4

Standard errors in parentheses. ***, **, * indicate statistical significance at the 99, 95 and 90% levels.

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